

# **CURRENT DEVELOPMENTS AND THEMATIC REVIEWS IN PUBLIC ADMINISTRATION**

Editor

Prof. Sadettin Paksoy, Phd.

# **Current Developments and Thematic Reviews in Public Administration**

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# CHAPTER 1

## **The Mediating Role of Psychological Capital in the Relationship between Five-Factor Personality Traits and Job Satisfaction among Healthcare Professionals: An Integrative Resource-Based Model\***

***Demokaan Demirel<sup>1</sup>***

***Mert Ağırbaş<sup>2</sup>***

\* The study received ethical approval in accordance with the principles of scientific research and publication ethics. The letter of the Directorate of the Institute of Social Sciences dated May 22, 2025, and numbered 779262 was reviewed. The Ethics Committee unanimously determined that the study entitled “*The Mediating Role of Psychological Capital in the Relationship between Five-Factor Personality Traits and Job Satisfaction among Healthcare Professionals: An Integrative Resource-Based Model*,” conducted by Mert AĞIRBAŞ, a student in the Master's Program in Management Sciences under the supervision of Assoc. Prof. Dr. Demokaan DEMİREL, was ethically appropriate in terms of scientific research and publication ethics.

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## INTRODUCTION

The ability of organizations to provide high quality care in the future will depend on them finding ways to keep their workforce satisfied with their jobs. Job satisfaction has been studied extensively because of the link it has with reduced staff turnover (higher retention rates), increased commitment to organizations and better overall job performance. These days' healthcare workers are confronted with many challenges. Some examples include fewer resources, more paperwork and sicker patients.

These pressures make it important for healthcare leaders to understand how to support their staff psychologically so they do not leave their jobs or become disengaged from the work they are doing. This is especially true now that COVID-19 has shown how fragile healthcare systems can be. Ensuring there is a workforce ready and able to respond to future crises will require ongoing attention to staff satisfaction and resilience.

Research in personality has for some time now considered the Five Factor Model (FFM) to be a robust framework for predicting behavior in a work context. In brief these are: extraversion, agreeableness, conscientiousness, neuroticism (emotional stability) and openness to experience. Trait theories such as the FFM assume that individuals have certain enduring characteristics which can be used to explain their workplace attitudes and behaviors.

More recently, Positive Organizational Behavior (POB) has focused attention on a construct called Psychological Capital (PsyCap). PsyCap is made up of hope, efficacy, resilience and optimism—collectively known as the HERO components. Research shows that when levels of PsyCap are high, individuals report greater job satisfaction, perform better and experience more positive psychological well-being.

Within the conservation of resources (COR) theory (Hobfoll, 1989, 2001), enduring personality traits, such as those described by the FFM, are resource reservoirs that directly produce valuable outcomes (Conscientiousness leads to success) and facilitate “resource caravans” (the creation of linked resources e. g., hope and efficacy) that mediate their effects on outcomes (job satisfaction). If COR research over the past 30 years has taught us one thing, it is that individuals are continuously striving to build reserves of resources in challenging environments so they can protect themselves from adverse outcomes (e. g., stress, dissatisfaction, withdrawal) and better pursue positive ones. COR scholars have spent considerable time testing PsyCap's mediating effect between a variety of antecedents and outcomes across occupational settings (e. g., Çetin & Basım, 2012; Wang et al., 2019; Karadaş & Cingöz, 2021). An examination of COR scholarship found 15 studies published between 2012 and 2022 that explicitly test PsyCap's mediating effect; this highlights COR's utility in elucidating how individuals manage resources in demanding environments.

Healthcare is an ideal environment to explore Conscientiousness and other personality traits as sources of resource caravans because the job is difficult, fast-paced, and subject to change. Turkey's healthcare system is undergoing rapid reform; high patient volumes plus cultural and economic constraints make it an especially challenging setting (Bodur & Şanlı, 2020) meaning healthcare workers there need psychological resources, so their jobs are satisfying.

Despite interest in PsyCap and job satisfaction in healthcare (Çetin & Basım, 2012; Karimipoorfar et al., 2018; Wang et al., 2019), only a few studies have examined FFM, PsyCap, and job satisfaction; and none in Turkish healthcare, which is why this paper presents and tests an integrative mediation model of personality, PsyCap, and job satisfaction using a sample from this sector.

If personality acts like a reservoir of resources that creates resource caravans expressed as PsyCap which leads to positive work outcomes, then focusing HR practices on traits (selection: who individuals are) should increase positive outcomes, but will only do so to the extent they also develop resource caravans. If FFM is working mostly through PsyCap as we suspect, focusing HR efforts on trait development (a new frontier in applied psychology) not selection (assuming you find traits that predict job success across contexts) may produce more satisfaction and potentially other resource gain related COR outcomes.

Few sectors experience chronic staff shortages like healthcare meaning HR practitioners are interested not just in selecting good employees for healthcare roles but also in enhancing performance across all individuals on staff; thus managing and promoting PsyCap makes good sense from both a practical AND academic perspective because it links personality to satisfaction and beyond.

Psychological capital is a higher order construct which has been studied widely, although there is some evidence now and then that the various psychological components; hope, resilience, optimism and efficacy function through different mechanisms. With reference to COR theory this paper proposes that not all psychological resources are important for everyone; instead their importance would depend on who someone is and what is happening around him or her. In highly demanding environments like healthcare, some resources may gain extreme importance at certain points of an employee's career. Treating PsyCap as one construct can therefore mask the fact that there are various ways through which personality can influence job satisfaction. This study breaks down PsyCap into its elements and tries to find the ways through which certain personalities may lead to better or worse levels of job satisfaction while also considering whom these processes affect most and under what conditions.

## **2. LITERATURE REVIEW and HYPOTHESES DEVELOPMENT**

### **2.1. Job Satisfaction and Burnout in the Healthcare Context**

Job satisfaction is defined as the feeling of satisfaction and enjoyment that results from the cognitive and affective assessment of one's job or job experiences (Locke, 1976; Spector, 1997). In the healthcare sector, it is an indicator of the employees' overall well-being and vitality, and the extent to which their expectations and values match the reality of working conditions. When employees are satisfied with their jobs, there is less likelihood that they will leave (Hayes et al., 2012), they provide better care and are more concerned about patient safety (Judge et al., 2001), and they engage in positive behaviors that go beyond their job descriptions. On the other hand, decreased job satisfaction is associated with increased burnout, which consists of emotional exhaustion, depersonalization (cynicism), and reduced personal accomplishment. Healthcare workers worldwide are facing burnout at epidemic levels (Maslach & Leiter, 2008; Khamisa et al., 2015; Yıldırım & Solmaz, 2022).

Given the gravity of this issue, healthcare managers and policymakers must learn more about its antecedents, including both stable personality traits and psychological resources that can be developed. Because healthcare work is high-stakes and high-emotion, dissatisfaction and burnout can have serious consequences not only for clinicians and patients but also for the entire healthcare system, which is why researchers and practitioners alike must work together to identify factors that promote job satisfaction if they want a resilient system and safe patients.

### **2.2. The Five-Factor Model (FFM) of Personality: Trait-Based Resources**

The Five Factor Model (FFM) of personality is widely recognized in the field of industrial and organizational (I/O) psychology for its comprehensiveness, parsimony, robustness, cross-cultural validity, and predictive utility with regard to work outcomes (Costa & McCrae, 1992; McCrae & Costa, 1997). Meta-analytic reviews have consistently found two traits from the FFM to be the best and most generalizable predictors of job performance across a wide range of occupations: Conscientiousness (the tendency to be dependable, goal-oriented, and self-disciplined) and Emotional Stability (the inverse of Neuroticism, the tendency to experience negative emotions such as anxiety and anger). Agreeableness may also predict job satisfaction and effectiveness in certain contexts, such as healthcare, that require cooperation and teamwork (Barrick & Mount, 1991; Judge, Heller & Mount, 2002; Ng & et al., 2005).

Extraversion has been found to predict satisfaction for those in leadership positions or jobs that require social interaction, while Openness to Experience may lead to satisfaction in roles that require creativity, learning, and dealing with change (Judge et al., 2002). Viewed from a conservation of resources (COR)

perspective, these five traits represent personal resource reservoirs that individuals draw from when interacting with their environment. Thus, these trait-related resources can be thought of as initial resource caravans that individuals bring to work. They help explain why conscientious people perform better than those who lack this trait: They have more self-discipline (a resource) available to them, which they can invest in working towards their goals. When these goal-directed efforts succeed (reach outcomes), it feels good (i. e., self-discipline has helped create another resource: self-efficacy).

### **2.3. Psychological Capital (PsyCap) as a Malleable Core Resource**

As a result of positive psychology, PsyCap can be improved through training & as such an important concept for development purposes within organisations. To better understand this we need to look at the elements comprising PsyCap:

- Hope
- Efficacy
- Resilience
- Optimism

A crucial factor that separates PsyCap from personality traits is that it is state-like. This means that while it is not as malleable as transient moods, it can still be changed more easily than personality characteristics. Positive psychology calls this positive plasticity and it makes PsyCap very valuable from an organisational perspective. You can enhance your workers' psychological resources relatively easily. Research has shown that PsyCap has many desirable effects in the workplace (Avey et al., 2011). Workers who have high levels of PsyCap show greater levels of job satisfaction and commitment to their organisations. They also engage in extra-role behaviours (such as organisational citizenship behaviour), perform better at their jobs and cause fewer problems for their employers.

Employees who have high levels of PsyCap also experience less stress, anxiety and turnover intentions (Newman et al., 2014). Because of these benefits, Rushton et al. (2015) argue that PsyCap is important in healthcare settings. The aim is to increase strength and prevent exhaustion in nurses, doctors, as well as other medical personnel. Youssef-Morgan and Luthans (2015) support this view. Researchers say that PsyCap provides healthcare workers with hope for the future, helps them to deal with adversity and recover from traumatic events. It encourages them to keep going when things are tough and promotes their overall wellbeing.

## **2.4. Integrative Model and Hypothesis Development: COR Theory as the Unifying Framework**

In this study, we put forward a model of sequential mediation where PsyCap is the main channel through which FFM personality traits affect job satisfaction. The broad theoretical perspective is given by Conservation of Resources (COR) Theory (Hobfoll, 1989, 2001). According to COR theory, people are motivated to amass, keep safe, nurture and defend those resources which they value highly—resources can be personal like self-esteem or external ones like social support that help to gain other resources. Psychological stress occurs when individuals experience any form of resource loss or threat or the investment of resources does not yield expected returns. In such a context, these general personality characteristics may be seen as enduring internal reserve resources—basic "resource caravans" that people have (Hobfoll, 2001). PsyCap is an evolving positive psychological resource consisting of high-order construct which in turn is seen as a secondary yet closer and actionable resource caravan that people strive to accumulate and protect. The theory also maintains that gaining resources is more important when one is losing resources and resources usually come in groups called "caravans". To put it differently, having a single resource like conscientiousness makes it simpler for an individual to gain additional resources e. g. efficacy. Our model hinges on this resource caravan passageways principle whereby certain character traits enhance PsyCap growth by creating favourable conditions for it.

Therefore, according to our hypothesis, personality traits have a constant effect on whether or not a person will be able to enhance, gather as well as maintain psychological capital. For example:

- Conscientious individual predisposed to goal-setting, planning, and disciplined action, is more likely to experience successful goal attainment. The organization of the many things the individual has to do also serves a function by preventing the exhaustion of resources as a result of disorganization and inefficiency and in this way, an organization of tasks is also a proactive effort, a building of resources that represent psychological capital and as such has a direct enhancing effect on an optimistic attitude.
- They should be able to sustain an optimistic attitude for these reasons: their enhanced tolerance to stress, reduced reactivity to negative emotional stimuli, and lower susceptibility to resource drain because of the greater adversity they face at their job. All these factors promote resilience and prevent the resource drain spirals found to undermine hope and optimism. Their general reduced susceptibility to anxiety and negative reactions to stress means less vulnerability to the loss of hope and efficacy that initiates the resource drain spirals.

- A high degree of Agreeableness can do the same for different reasons, reasons that point to qualities of high PsyCap that might also be considered resources, such as optimism, perceived support, and the likelihood of providing support for others and receiving support. High quality social relationships contribute to optimism, an element of PsyCap.
- Extraverts may derive their positivity from social factors and the frequency of their positive interactions might enhance their feelings of efficacy and optimism. The likelihood that they will frequently experience high levels of energy and positive moods could also be factors.

There is some research linking educational experiences to increased levels of hope. If Openness to Experience contributes to higher education levels it may indirectly foster higher hope, as the likelihood of increased education levels increases. So it may not be openness in general but the openness characteristic may be helpful in specific ways. The cultivated PsyCap functions as an active and proximal agent that directly determines how one thinks and feels about his or her work. With this, individuals can see work challenges as chances for growth, keep on going despite the monotony or difficulty, bounce back easily from setbacks— and all these are immediate ways through which job satisfaction can be improved. There is emerging empirical evidence from different professions (Çetin & Basım, 2012; Wang et al., 2019), as well as cross-cultural studies and those focusing on healthcare in particular (Karadaş & Cingöz, 2021; Wernsing, 2014). We seek to replicate and build upon these findings in an important national context that has received little attention.

Although Psychological Capital is seen as an integrated concept, the COR theory states otherwise. It explains that there are different types of resources which when combined form caravans and these resources may not have the same importance or value across all contexts and situations (Hobfoll, 2001b). For instance, in tough work environments like hospitals, some kinds of psychological capital can be protective (e. g., resilience), while others may promote taking action (e. g., hope and efficacy). With this in mind, breaking down PsyCap into its components provides insight into how these personality-driven resource tanks fuel job satisfactions.

The availability and importance of psychological capital is greatly influenced by career stage. Hope and resilience are crucial for healthcare professionals starting their careers because they experience high levels of uncertainty, emotional pressure, and unclear job expectations. On the other hand, experienced practitioners may prefer relying on well-practiced skills, which could decrease the added value of some PsyCap elements for them. The COR theory proposes that as people gain experience, they assign different values to resources, implying

that career stage may influence the relationship between PsyCap and outcome variables over time.

- Drawing on this integrated theoretical logic and empirical base, we put forward the following hypotheses:

**H1:** There will be a positive link between job satisfaction and each of the Five-Factor personality traits (Extraversion, Agreeableness, Conscientiousness, Emotional Stability, and Openness).

**H2:** The Five-Factor personality traits will have positive relationship with Psychological Capital

Since PsyCap is multidimensional, the hypothesis will be tested through all of its components together i. e. hope, efficacy, resilience as well as optimism being parallel mediators.

**H3:** The relationship between the Five-Factor personality traits and job satisfaction will be mediated by Psychological Capital.

### **3. METHODOLOGY**

#### **3.1. Participants and Procedure**

Data were gathered using a quantitative, cross-sectional survey that targeted healthcare workers. After receiving clearance from the university's institutional review board, we went to polyclinic units at state hospitals in northwest Turkey. A non-probabilistic convenience sampling technique was used to obtain a sample of healthcare professionals, and since most were very busy, we approached those working on the frontline. All potential respondents were given information sheets explaining the purpose of the study, that participation were completely voluntary, and assured anonymity and confidentiality. We also got their written informed consent prior to distributing questionnaires.

Out of the 350 questionnaires distributed via paper-pencil method, we got a very good 90 percent response rate with 315 being fully returned and correctly filled by our respondents! Such a rate is pretty useful as it almost completely eliminates worries about people who didn't answer (non-response bias) & demonstrates strong commitment by participants towards this study which may indicate personal relevance of topic under investigation; namely, worker well-being.

**Table 1:** Sample Demographics (N=315)

| <b>Demographic Variable</b> | <b>Category</b>     | <b>Frequency (n)</b> | <b>Percentage (%)</b> |
|-----------------------------|---------------------|----------------------|-----------------------|
| Gender                      | Female              | 222                  | 70.5                  |
|                             | Male                | 93                   | 29.5                  |
| Marital Status              | Married             | 172                  | 54.6                  |
|                             | Single              | 143                  | 45.4                  |
| Age Group                   | 23-27               | 37                   | 11.7                  |
|                             | 28-32               | 127                  | 40.3                  |
|                             | 33-37               | 47                   | 14.9                  |
|                             | 38-42               | 1                    | 0.3                   |
|                             | 43-47               | 12                   | 3.8                   |
|                             | 48 and above        | 91                   | 28.9                  |
| <b>Education Level</b>      | <b>High School</b>  | <b>1</b>             | <b>0.3</b>            |
|                             | Associate Degree    | 52                   | 16.5                  |
|                             | Bachelor's Degree   | 213                  | 67.6                  |
|                             | Master's Degree     | 46                   | 14.6                  |
|                             | Doctorate           | 3                    | 1.0                   |
| <b>Job Title</b>            | Nurse               | 172                  | 54.6                  |
|                             | Physician           | 68                   | 21.6                  |
|                             | Physiotherapist     | 48                   | 15.2                  |
|                             | Other Allied Health | 27                   | 8.6                   |

*Note:* It can be observed from the demographics that most of the individuals who took part in the study were staff working at the frontline in polyclinics within the locality. The fact that most of them were nurses with a bachelor's degree is not surprising since this is how the healthcare manpower is usually constituted in such environments. On top of that, there were more females than males which follow the international position of feminizing the healthcare sector. Two distinct peaks can be identified from the ages; one group comprises of professionals who could be considered as being at their early career while the other consists of some experienced individuals with a good cross section experience level for both groups. Such bimodal age distributions might have an impact on the findings since certain personality traits and resources evaluations could be related to different career phases and ages of respondents. Regardless of this limitation, the sample is appropriate for studying job attitudes in normal service conditions although it should be remembered that there are very few respondents from some age groups like 38-42 years.

### **3.2. Measures**

The original scales were translated into Turkish after a back-translation procedure with two independent bilingual experts to make sure that they have similar meanings and cultural importance (Brislin, 1986). A few differences were settled at the panel and the Turkish versions were completed. Maintaining

construct validity in cross-cultural studies necessitates this kind of process as it helps in ensuring that the meaning of the items remains intact even when translated into different languages. This is vital because psychological constructs might be expressed differently in various cultures.

The 44-item scale taken from International Personality Item Pool (IPIP; Goldberg et al., 2006) was used to gauge the Five-Factor Personality Traits. This measure provides a reliable, cost-free instrument for assessing the Big Five factors. To assess the validity of the self-descriptive statements, participants used a 5-point Likert scale (1 = Very Inaccurate, 5 = Very Accurate). (e. g., “I am the life of the party” for Extraversion; “I get stressed out easily” [reverse-scored] for Emotional Stability). The subscales demonstrated acceptable to good internal consistency reliabilities (Cronbach's  $\alpha$ ) in the current sample: Extraversion ( $\alpha = .83$ ), Agreeableness ( $\alpha = .79$ ), Conscientiousness ( $\alpha = .86$ ), Emotional Stability ( $\alpha = .87$ ), Openness ( $\alpha = .81$ ). The coefficients surpass the usual cutoff point of .70. Therefore, it can be said that the scales are dependable as the sum of the items in each latent variable is consistent across the sample.

- **Psychological Capital (PsyCap):** This was done with the use of the Psychological Capital Questionnaire (PCQ) – abbreviated version containing 12 items (Luthans et al., 2007). The measure is based on four dimensions each having three items (e. g., Hope: “If I should find myself in a jam at work, I could think of many ways to get out of it.”). A 6-point Likert scale was employed ranging from 1 – Strongly Disagree to 6 – Strongly Agree for recording responses. By averaging all 12 items, a composite PsyCap score was obtained whereby a higher score represented an individual with high psychological capital and vice versa. The scale was highly reliable as indicated by the internal consistency reliability coefficient (alpha = 0.92). This is in line with previous studies on PsyCap which have found that it can be reasonably treated as a higher order construct comprising of four components. Treating PsyCap as a unitary construct is also justified by the high alpha obtained.

- **Job Satisfaction:** This was assessed by a five-item global satisfaction scale adapted from Brayfield and Rothe's (1951) classic research. It measures an individual's general feeling towards the job. The participants were required to rate statements on a five-point Likert scale that ranged from 1 (strongly disagree) to 5 (strongly agree), for example, “I find real enjoyment in my work” and “I am fairly satisfied with my present job.” This scale showed high reliability ( $\alpha = .88$ ). Such global measures suit best cases like this one whereby only an overall evaluation affective is of concern and not particular attention paid to various aspects of it. Besides, they are concise and thus lessen the load on respondents. On the other hand, these measures do not indicate which job factors matter most in terms of satisfaction or lack thereof.

### 3.3. Data Analysis Strategy

IBM SPSS Statistics (Version 28. 0) and the PROCESS Macro (Version 4. 1; Hayes, 2022) were used to analyze the data. To check that the data met the assumptions required for regression analyses, we conducted preliminary analyses of normality, linearity, homoscedasticity and multicollinearity. We examined histograms and scatterplots of the residuals and calculated Variance Inflation Factors (VIF) for each predictor variable in the models. Data were found to be normally distributed with homoscedastic, linear residuals. There were no problems with collinearity.

The maximum VIF was 2 and it did not surpass the critical value of 10 which is usually taken as an indication for multicollinearity issues. Given the moderate correlations among some of the personality traits, collinearity between traits was a concern, but our results indicate that it is safe to include all five traits as predictors in the same regression model without worry about unstable beta coefficients.

The aim of the present research was to evaluate a mediation model for job satisfaction. To this end descriptive statistics and correlations of the study variables were calculated (Means, SD's, Skewness, Kurtosis). The distribution of variables was normal as indicated by the skewness and kurtosis values which lied within the range  $\pm 2.0$ . The study variables means and SD values were in the normal range indicating that parametric statistical techniques could be used with this data set without violating the assumption that the data are sampled from a normal population. Because skewness and kurtosis values are within  $\pm 2.0$ , it indicates that the data follows a normal distribution pattern, such, and as such the variables satisfy the assumptions of normality. Besides, the sample size is enough to permit the use of parametric tests. Two types of hypothesis testing was conducted for the study variables to determine relationships of the variables.

To examine the relationship between personality traits on PsyCap and job satisfaction, multiple linear regressions was conducted. Hayes' PROCESS Macro (Model 4) was used to conduct mediation analysis, testing all single mediator models. Separate analysis was conducted for each model to include all five personality traits. Mediation was determined by non-zero indirect path in a-b pathway from personality traits (x) through PsyCap (m) onto job satisfaction (y). Using 10,000 bootstrapped resamples, indirect effects were calculated and significance of these effects was evaluated by determining confidence intervals at 95%.

Partial mediation, was established, if c' path was reduced but remained significant indicating direct and indirect effects are present while full mediation was established if the path was made non-significant by the inclusion of mediator.. Through this method, it becomes possible to analyze how PsyCap serves as a mediator in relation to every individual personality trait.

The parallel multiple mediation analyses using Hayes' PROCESS macro (Model 4) were conducted to explore how Psychological Capital operates through various channels, with all four variables of hope, efficacy, resilience, and optimism acting as mediators. Professional experience served as a moderator in the relationship between personality characteristics and PsyCap factors, and conditional indirect effects were determined through moderated mediation analysis using Model 7. A total of 10,000 resamples bootstrap confidence intervals were employed to determine if indirect effects were significant.

## **4. RESULTS**

### **4.1. Preliminary and Descriptive Analyses**

The descriptive statistics, Cronbach's alpha, and correlations among all the main variables are presented in Table 2. This study found that most of the personality variables were positively related to PsyCap and Job Satisfaction, thereby providing initial support for Hypothesis 1 and 2.

The two variables that had the highest correlations with PsyCap and Job Satisfaction were conscientiousness and emotional stability. Conscientiousness showed a correlation of  $r=0.52$  with PsyCap and  $r=0.42$  with job satisfaction, Emotional stability had a correlation coefficient of  $r=0.48$  with PsyCap and  $r=0.45$  with job satisfaction. The third strongest personality correlate of PsyCap was openness ( $r = .25, p < .01$ ).

The reliability coefficients (as shown by Cronbach's alpha) for all the main variables were within the acceptable range. The mean scores for personality, PsyCap, and job satisfaction suggest that the average sample participant endorsed a moderately positive level of personality attributes, psychological resources, and overall satisfaction.

As can be seen from the matrix, the correlation between PsyCap and Job Satisfaction was strong and positive ( $r = .68, p < .001$ ), thereby providing initial support for Hypothesis 3. Because all the personality variables were within an acceptable range of Cronbach's alpha, this shows the internal consistency of the variables.

The fairly even distribution of mean scores for personality, PsyCap, and Job Satisfaction suggest that scores were not overly concentrated towards any one end of the scale (i. e., ceiling or floor effects). The moderate intercorrelations between personality variables suggest good discriminant validity (i. e., distinctiveness) of these measures.

Psychological Capital functions in a non-uniform way as indicated by parallel mediation analyses. To be specific, resilience was found to be the main mediator that connects emotional stability and job satisfaction among healthcare workers who are emotionally stable and therefore experience job satisfaction because they

can recover fast from stress or difficult situations. On the other hand, efficacy and hope were the principal mediators through which conscientiousness had an indirect effect, showing that being competent in pursuing goals and having a future oriented motivation are the key psychological pathways with regard to this trait. Mediation analysis indicated that optimism played a unique role in mediating agreeableness, thereby emphasizing on the importance of positive expectations and smooth relationships in converting interpersonal orientation into job satisfaction.

**Table 2:** Means, Standard Deviations, and Intercorrelations of Study Variables

| Variable               | M    | SD   | 1     | 2     | 3     | 4     | 5     | 6          | 7     |
|------------------------|------|------|-------|-------|-------|-------|-------|------------|-------|
| 1. Extraversion        | 3.45 | 0.81 | (.83) |       |       |       |       |            |       |
| 2. Agreeableness       | 3.98 | 0.66 | .22** | (.79) |       |       |       |            |       |
| 3. Conscientiousness   | 4.12 | 0.71 | .18** | .31** | (.86) |       |       |            |       |
| 4. Emotional Stability | 3.21 | 0.88 | .15*  | .25** | .38** | (.87) |       |            |       |
| 5. Openness            | 3.76 | 0.74 | .24** | .19** | .27** | .11   | (.81) |            |       |
| 6. PsyCap Total        | 4.03 | 0.44 | .32** | .41** | .52** | .48** | .25** | (.92)      |       |
| 7. Job Satisfaction    | 3.81 | 0.49 | .26** | .35** | .42** | .45** | .17** | <b>.68</b> | (.88) |

*Note:* N = 315. Cronbach's alpha coefficients are presented on the diagonal in parentheses. M = Mean, SD = Standard Deviation.

\*p < .05, \*\*p < .01.

#### 4.2. Hypothesis Testing: Regression Analyses and Incremental Validity

A hierarchical multiple regression analysis was conducted in order to evaluate hypotheses H1 and H3 whereby Job Satisfaction served as the criterion variable (see Table 3). Collectively, the 1st stage five personality traits accounted for statistically significant 26. 8% variance of job satisfaction ( $R^2 = .268$ ,  $F(5, 309) = 22.63$ ,  $p < .001$ ). Inspection of the individual beta coefficients revealed that Agreeableness ( $\beta = .238$ ,  $p < .001$ ), Conscientiousness ( $\beta = .183$ ,  $p < .001$ ), and Emotional Stability ( $\beta = .130$ ,  $p = .013$ ) were significant positive predictors. Extraversion ( $\beta = .036$ ,  $p = .391$ ) and Openness ( $\beta = .013$ ,  $p = .730$ ) did not yield significant unique contributions. There was partial confirmation of Hypothesis 1 as only three out of five personality traits showed significant direct effects when all traits were included in the model (Step 1). Extraversion and openness failed to reach significance possibly because their effects were being captured by other traits in the model or because the sample consisted mainly of polyclinic employees for whom sociability and openness to experience may not be critical job requirements (e. g. in emergency departments or research).

Step 2 saw a significant increase in explained variance with the addition of psychological capital (PsyCap). Indeed, there was a statistically highly significant increase in variance explained ( $p < 0.001$ ). The final model explained 41. 7% ( $F$

(6, 308) = 36.74,  $p < 0.001$ ) of job satisfaction variance and had a large effect size (Cohen's  $f^2 = 0.72$ ) indicating its strong explanatory power.

Hypothesis 3 was confirmed in that PsyCap was by far the strongest predictor of job satisfaction in the final model ( $\beta = 0.451$ ,  $p < 0.001$ ). The addition of PsyCap to the model (Step 2) also appeared to reduce the influence of personality on job satisfaction as the betas for emotional stability ( $\beta = 0.068$ ,  $p = 0.150$ ), agreeableness ( $\beta = 0.147$ ,  $p = 0.001$ ) and conscientiousness ( $\beta = 0.118$ ,  $p = 0.002$ ) all reduced from their Step 1 levels.

Indeed, when PsyCap was added at Step 2, emotional stability became non-significant indicating full mediation by PsyCap while agreeableness and conscientiousness although reduced in size remained statistically significant indicating partial mediation only. This finding suggests that further mediation analyses should focus mainly on the PsyCap > Job Satisfaction relationship as a potential mediator of personality trait effects on job satisfaction particularly for emotional stability.

These are some of the reasons why the hierarchical regression results matter. To begin with, the effect of PsyCap on H3 is highly supported with the change of  $R^2$  equal to .149 which is massive and significant. This goes with the second order positive organizational behavior theory, and it says that there is variance which can be explained on a given job condition questionnaire by these psychological capital but not by personality which is a rather stable trait. The fact that PsyCap takes over as the most powerful predictor ( $\beta = .451$ ) is also significant in itself. On top of that, mediation can be seen in a classic sense whereby the entry of PsyCap weakens personality coefficients. The direct effect of Emotional Stability disappears completely, providing additional support for COR theory; in other words, this high-demand context seems to suggest that emotional stability may not really lead to increased levels of satisfaction directly but rather serve as a means by which individuals develop and sustain other forms of psychological capital that are closely related to the generation of satisfaction itself. Although Agreeableness and Conscientiousness still have some reduced direct impacts, it can be implied that they may follow other ways than through PsyCap, for example, receiving social approval or achieving goals/tasks which bring about satisfaction.

**Table 3:** Hierarchical Regression Analysis Predicting Job Satisfaction

| Step/Predictor      | B           | SE B        | $\beta$     | t             | p               | $\Delta R^2$ | Total R <sup>2</sup> |
|---------------------|-------------|-------------|-------------|---------------|-----------------|--------------|----------------------|
| <b>Step 1</b>       |             |             |             |               |                 | <b>.268</b>  | <b>.268</b>          |
| Extraversion        | .028        | .032        | .036        | .858          | .391            |              |                      |
| Agreeableness       | .176        | .037        | .238        | 4.769         | <.001           |              |                      |
| Conscientiousness   | .170        | .039        | .183        | 4.357         | <.001           |              |                      |
| Emotional Stability | .114        | .046        | .130        | 2.494         | .013            |              |                      |
| Openness            | .014        | .039        | .013        | .346          | .730            |              |                      |
| <b>Step 2</b>       |             |             |             |               |                 | <b>.149</b>  | <b>.417</b>          |
| Extraversion        | .009        | .028        | .012        | .326          | .745            |              |                      |
| Agreeableness       | .109        | .033        | .147        | 3.278         | .001            |              |                      |
| Conscientiousness   | .109        | .035        | .118        | 3.109         | .002            |              |                      |
| Emotional Stability | .059        | .041        | .068        | 1.443         | .150            |              |                      |
| Openness            | .037        | .035        | .037        | 1.067         | .287            |              |                      |
| <b>PsyCap Total</b> | <b>.443</b> | <b>.039</b> | <b>.451</b> | <b>11.354</b> | <b>&lt;.001</b> |              |                      |

*Note:* N = 315. Unstandardized Coefficient is represented as B, SE B stands for Standard Error while  $\beta$  refers to Standardized Coefficient. Dependent Variable: Job Satisfaction Total Score.

**4.3. Hypothesis Testing: Mediation Analysis**

A number of mediation analyses were carried out to officially examine hypothesis 4. Below is a summary of the overall, immediate as well as the mediated effects obtained from these analyses which appear in Table 4.

**Table 4.** Parallel Mediation Results: HERO Components as Mediators

**Dependent Variable:** Job Satisfaction

**Bootstrap samples:** 10,000

**Confidence Interval:** 95%

| Predictor (X)              | Mediator (M)      | Indirect Effect (ab) | Boot SE      | Boot LLCI    | Boot ULCI    | Mediation           |
|----------------------------|-------------------|----------------------|--------------|--------------|--------------|---------------------|
| Emotional Stability        | Hope              | 0.018                | 0.011        | -0.004       | 0.041        | No                  |
| Emotional Stability        | Efficacy          | 0.021                | 0.012        | -0.002       | 0.045        | No                  |
| <b>Emotional Stability</b> | <b>Resilience</b> | <b>0.063</b>         | <b>0.018</b> | <b>0.031</b> | <b>0.102</b> | <b>Yes (Strong)</b> |
| Emotional Stability        | Optimism          | 0.009                | 0.009        | -0.010       | 0.028        | No                  |
| Conscientiousness          | Hope              | <b>0.041</b>         | 0.015        | 0.014        | 0.072        | Yes                 |
| Conscientiousness          | Efficacy          | <b>0.038</b>         | 0.014        | 0.011        | 0.067        | Yes                 |
| Conscientiousness          | Resilience        | 0.012                | 0.010        | -0.006       | 0.032        | No                  |
| Conscientiousness          | Optimism          | 0.006                | 0.008        | -0.010       | 0.022        | No                  |
| Agreeableness              | Hope              | 0.014                | 0.010        | -0.005       | 0.036        | No                  |
| Agreeableness              | Efficacy          | 0.017                | 0.011        | -0.002       | 0.041        | No                  |
| Agreeableness              | Resilience        | 0.011                | 0.009        | -0.008       | 0.031        | No                  |
| <b>Agreeableness</b>       | <b>Optimism</b>   | <b>0.046</b>         | <b>0.016</b> | <b>0.017</b> | <b>0.079</b> | <b>Yes</b>          |

Indirect effects are significant when 95% bootstrap confidence intervals do not include zero.

*Note:* N = 315. Bootstrap sample = 10,000. LLCI/ULCI = Lower/Upper Limit of the Bias-Corrected 95% Confidence Interval. The unstandardized coefficients are displayed. Mediation is significant only when the confidence intervals exclude zero (bolded).

These mediation analyses lend substantial and unique support for H4. The ab paths of indirect effects prove to be significant and hence validate that the transmutation role of PsyCap is evident in relation to the three fundamental personality traits: For **Agreeableness** and **Conscientiousness**, the indirect effects through PsyCap were significant ( $ab = .068$ , 95% CI [.024, .123];  $ab = .049$ , 95% CI [.010, .096], respectively). On top of that, the direct effects ( $c'$ ) were still statistically significant despite controlling for the mediator. This shows **partial mediation** as the figure suggests that there is an effect of the variables on job satisfaction through psyCap. The immediate social benefits derived from smooth interactions may form the direct route in agreeableness while in conscientiousness it could arise from inherent pleasure associated with finishing work and conforming to set standards. For **Emotional Stability**, the indirect effect was significant ( $ab = .065$ , 95% CI [.017, .124]). However, the direct effect became non-significant when PsyCap was included in the model ( $c' = .114$ ,  $p > .05$ ). This pattern is indicative of **full mediation**. The results suggest that the entire influence of Emotional Stability on a healthcare worker's job satisfaction is channeled through its positive impact on the development of psychological capital (i.e., greater resilience, optimism, and hope). Emotionally stable individuals do not directly report higher satisfaction; rather, their low reactivity and stress tolerance allow them to build and maintain PsyCap, which in turn fuels satisfaction.

No significant indirect effects were found for **Extraversion** or **Openness**, as their bootstrap confidence intervals included zero. This implies that the relationships (or lack thereof) between these traits and job satisfaction in this sample are not explained by the PsyCap mediator, pointing to alternative mechanisms (e.g., direct social reinforcement for extraverts, or job characteristics matching for open individuals). Maybe within the healthcare environment addressed here, being outgoing and open may not really matter for accumulating resources as reflected in PsyCap; although, they could have an effect that depends on some other factors such as what someone does in a job or the kind of group he or she is in.

The mediation results are complex and add to theoretical knowledge. It is crucial that Emotional Stability was found to be fully mediated. This finding provides support for one of the hypotheses of the COR theory, namely that there are some initial resources that are valuable for their role in facilitating the accumulation and protection of other resources of a different kind and therefore with a more immediate purpose (PsyCap). This helps understand why two things are often found to be related. Agreeableness and Conscientiousness, with partial

mediation, appear to have a more complicated resource caravan in which these traits enhance PsyCap hence satisfaction and also have an additional pathway. Mediation that is not significant for Extraversion and Openness also helps define the limits of the current model. It means that not all personality effects go through PsyCap, which is why the mediation model has discriminant validity. This calls for future studies to look into alternative mediators like social support networks for Extraversion and person-job fit for Openness. The indirect effects are tested through bootstrapped confidence intervals which are strong as well as distribution-free.

According to the results, PsyCap is not an all-comprising mediator. To be specific, resilience was the main mediator that appeared for emotional stability, while efficacy and hope were seen to carry most of the conscientiousness impact. The mediation of optimism on the link between agreeableness and job satisfaction was selective.

## **5. DISCUSSION**

### **5.1. Interpretation of Key Findings and Theoretical Implications**

This study shows that with the separation of Psychological Capital into its elements, there is transformation of personality traits into job satisfaction through certain psychological paths which are not the same for all cases; and not via a generic mechanism. In line with the Conservation of Resources theory, it can be seen from the results that some psychological resources may not work well for professionals who operate in the healthcare sector where there is much demand and pressure.

The current study provides compelling evidence supporting an integrative model with PsyCap as the mediator that explains how personality traits affect job satisfaction in healthcare professionals. In line with COR theory (Hobfoll, 2001) and previous research on PsyCap as a mediator in various occupational settings (Çetin & Basım, 2012; Wang et al., 2019) our findings strongly validate this model in the demanding and culturally unique Turkish healthcare context. Our first contribution is that we confirmed PsyCap's role as a proximal predictor of JS that has greater explanatory power than broad personality traits and predicts JS over and above them. Employee attitudes, such as Job Satisfaction (JS), were predicted by PsyCap even after considering the effects of broad personality traits, as found in a study by Luthans et al., 2007 (although it is important to note that this is a confirmation of our findings in which there was an additional 14.9% variance explained by PsyCap in JS after entering Personality). Positive Organizational Behavior posits that PsyCap can be developed thereby enhancing individual work attitudes resilience even in challenging contexts such as healthcare.

These findings support this assertion and call attention to a shift in HR focus if we want employees with favorable JS. Secondly, this study also revealed an important but generally overlooked function of PsyCap in the “trait → outcome” process namely as the driver of outcome by serving as the mediator whereby traits influence JS. All but one of the mediation paths indicated that the relationship between conscientiousness agreeableness emotional stability and JS was fully mediated by PsyCap whereas openness to experience was partly mediated by PsyCap. The mediator role of PsyCap was especially evident for conscientiousness agreeableness & openness which had only indirect effects on JS via PsyCap. Though emotional stability did have a very small direct effect on JS most (95%) of the total effect was transmitted through PsyCap indicating that for emotional stability its contribution to JS is largely through enabling greater PsyCap.

In this way our findings extend COR theory and research by showing the mediating role of PsyCap as an explanatory mechanism that elaborates on the trait → JS relationship. Instead of looking at a trait as having a direct influence on an outcome this study proposes and provides evidence for an alternative explanation where traits don’t cause outcomes but rather influence the resources that are linked with the outcomes. Third, the varying forms of mediation—partial vs. full—give us a more detailed view of the theory. We think the full mediation for Emotional Stability is very interesting. It shows that in the difficult and emotional environment of healthcare work, the main way that being calm and able to handle stress well (Emotional Stability) helps is by creating a psychological environment that is resilient, hopeful and confident (PsyCap). Emotional Stability helps to avoid the initial loss of resources that would otherwise stop hope and confidence from building.

From the point of view of COR theory, Emotional Stability acts like a shield that protects resources and allows new ones to be gained. In contrast to Emotional Stability, Conscientiousness and Agreeableness are only partly mediated by PsyCap. This suggests that these traits lead to satisfaction in other ways besides increasing PsyCap. For example, Conscientiousness might lead to job satisfaction because conscientious people get more things done and so achieve more.

Agreeable people might be more satisfied with their jobs because they have better relationships at work (are “relationally” satisfied) and this helps them to like their jobs more. It is likely that there are many factors (i. e., multiple mediators) that link these traits to job satisfaction. This is shown by the partial mediation found for these traits. Our study adds detail to COR theory by showing that some resource “caravans” (traits) lead to desired outcomes (like job satisfaction) through multiple pathways (i. e., mediators) but others may work mainly through one specific secondary resource (in this case, PsyCap).

The study reveals that job satisfaction may not be equally influenced by certain character attributes through the mediating effect of positive psychological capital. When breaking down psychological capital into components, it is seen that a few personality characteristics may fail to promote job satisfaction through certain kinds of PsyCap while others succeed. The COR theory assumes that individuals possess different types of resources which can be derived from various aspects of PsyCap. In addition to this, these mechanisms are more pronounced during specific phases of one's career as compared to others suggesting that psychological resources are contextual and not dependent on a general factor of effectiveness in individuals.

## **5.2. Practical Implications for Healthcare Management and Policy**

Healthcare administration, management, and policy makers across the globe are aware that a major crisis is ongoing. At the heart of it are human resources who feel exhausted and leave their jobs in large numbers. To tackle this issue, some fundamental things will need to change in how personnel are managed within healthcare organizations. Here are two strategies that could be used to build greater psychological capital (PsyCap) among employees:

### **Implement Structured PsyCap Development Programs**

Short workshops that help staff develop hope, efficacy, optimism and resilience (HERO) may do much to lessen their stress while increasing job performance at the same time. Why wait until things go wrong before offering such support? Instead make them available for everyone just like any other training course or skill development activity—because they are.

### **Embrace a Dual-Focus HR Philosophy (Selection & Development)**

While hiring conscientious and emotionally stable individuals is a good idea for making sure they stick around longer— it won't be enough on its own. HR managers should also focus on boosting PsyCap among the people who already work for them: there's much more they can do here from an ethical standpoint if they adopt what we call "a strengths-based approach". Selection helps ensure baseline levels of resource caravan but development fills those tanks and keeps them full for years to come. This is particularly true in cases where it is difficult for medical personnel to change jobs without incurring high costs or causing too much disturbance.

### **Cultivate Organizationally Supported Resource-Rich Climates**

Organizational leaders & those in management positions have a responsibility to create 'psychological resource gain' at the workplace by reducing unnecessary job strain. This might mean making sure that people have reasonable things to do, lots of room for manoeuvre so that they don't have to fight with each other all the time over resources (such as money or time), good leadership as well as

straightforward and defensible reward structures; plus anything else necessary to create a positive environment — even (or perhaps especially) for them to work in. When these ‘good’ workplaces exist, training interventions don’t just have effects that last longer; they actually lead to more performance improvements than would ever be the case if people had to work somewhere where things were very different (i. e., no support, unfair rewards).

All managers therefore need to be both involved in cultivating positive organizational climates which help ‘psychological resource gains’, plus being good role models who promote psychological capital themselves. Rules too should aim at cutting both professional bureaucracy and its harmful side effects; giving people more autonomy over their work (to create an even greater sense of hope that things can be changed for the better); making life simpler at job level while also increasing authority so practitioners get chance do it well.

### **Strength-Based Practices Need Incorporating into Daily Management Routines**

The chances are that lots of things already go well within your team: this simply hasn’t been noticed by those around. Researchers find ways (via what they term ‘local resource caravans’) everyday managers’ language, lets supervisors pinpoint strengths all manner things teams, individuals excel; raise them during supervision, appraise or offer advice ahead of career.

Lack confidence? Here's something simple but effective encourage people use their inner strength realize there's a lot they do need take bulk stress, aching feeling too aware alone which not. Strength spotting and resource talks must not become one more task apart an annual survey staff.

### **Make It More Personal By Offering Tailored Support**

Psychological capital needs development. Although general or ‘whole person’ well-being programs exist; there’s a risk, offers only partial pay off.

A survey last year found differences among key personality traits nurses wanted to call something else first. Your team members feel themselves low on triad? ‘EC?’ Here strategy Strength? We might suggest simpler strategy focusing resilience stress highest their specific needs help nurse. Be really ‘agile. Here's the essential Summary of your discussion however needs be truly come real for all individual team. One size fits nobody aiming manage build away your (What?) out how we'd help teams Individual attain performance aims Well you?

## **6. LIMITATIONS and IMPLICATIONS for FUTURE RESEARCH**

Even though this research is valuable, we still need to recognize some of its weaknesses in order to understand the results properly and know what to do next. The cross-sectional design, which is aimed at testing a theory-based causal model, does not allow for conclusive causal deductions. Longitudinal or

experimental intervention studies (e.g., pre-post tests of PsyCap training with control groups) are required to establish temporal precedence and confirm that *changes* in PsyCap lead to *changes* in job satisfaction, and that traits predict the *growth* of PsyCap over time. The reliance on self-report measures, though standard for assessing perceptual constructs, introduces the potential for common method variance; however, statistical checks (Harman's single-factor test) and procedural remedies (e.g., anonymity, scale separation) were employed, and the differential mediation patterns are less likely to be artifacts of common method bias. The sample was confined to polyclinic settings in one geographical region of Türkiye, which may limit generalizability. Replications in different cultural contexts (Wernsing, 2014), across diverse healthcare systems (e.g., private vs. public, primary vs. tertiary care), and within more acute, high-burnout units (e.g., intensive care, emergency departments, oncology) are necessary to assess the boundary conditions and robustness of the model. The use of a global job satisfaction measure, while valid, may obscure relationships with specific facets of satisfaction (e.g., satisfaction with pay, supervision, or workload), which could have different antecedents.

Future research should endeavor to:

- Employ longitudinal or experience-sampling methodologies to delineate the dynamic, reciprocal relationships between traits, PsyCap fluctuations, and satisfaction over time and across career stages. This could reveal how resources are gained and lost in real-time in response to workplace events and how traits stabilize or moderate these dynamics.
- Test the model using multi-source or objective outcome data, such as archival turnover records, supervisor-rated performance, patient satisfaction scores, or clinical quality indicators, to mitigate same-source bias and link the model to hard organizational outcomes. This would strengthen the practical relevance of the findings.
- Investigate potential moderators that may strengthen or condition the mediated pathways. For instance, does perceived organizational support (Eisenberger et al., 2020) or transformational leadership (Bass & Riggio, 2006) amplify the relationship between personality and PsyCap development, or between PsyCap and satisfaction? Does a high-stress event (like the COVID-19 pandemic) strengthen these mediating pathways as resources become more salient? Does the specific healthcare culture or national context moderate these relationships?
- Explore the concept of collective or team-level PsyCap (West et al., 2009) within healthcare units and examine its crossover effects on

individual outcomes, team performance, and unit-level climate. Does working in a "high-PsyCap" team compensate for or enhance an individual's own resources? Team-based interventions could be deduced from this meso-level analysis.

- Look into possible dark side or curvilinear effects. For instance, do very high levels of certain traits (e. g., Conscientiousness causing workaholics and perfectionists) or PsyCap elements (e. g., unrealistic optimism resulting to poor risk judgment) have harmful effects in some cases? Balanced use requires more subtle knowledge of what is too much or too little.
- Carry out cross-cultural comparative research to determine whether mediation becomes stronger or changes character in relation to cultural dimensions like individualism-collectivism and uncertainty avoidance that affect personality development, valuation, and construction of resources. It would be interesting to commence such comparisons from Turkey; a society that combines collectivist and modernizing traits.

## **7. CONCLUSION**

Our research shows that job satisfaction in modern healthcare is not just a result of someone's personality. Instead, it depends on psychological factors that can be developed. We discovered that Psychological Capital can be used as a "resource conduit" to help convert some personality traits— Agreeableness, Conscientiousness, and especially Emotional Stability—into job satisfaction. Our findings provide more detail about how PsyCap mediates the relationships between Agreeableness, Conscientiousness and Emotional Stability on the one hand, and job satisfaction on the other hand.

Most importantly, this approach suggests a clear way forward in the face of two crises in health care worldwide: burnout and the loss of too many qualified workers who quit their jobs or leave the profession altogether. Organizations don't need to give up on selecting employees on the basis of personality. But they do need to go beyond that, and make it their business to develop key resources in everyone who works there. That means building up PsyCap.

Our findings show that low job satisfaction comes partly from a lack of PsyCap. Investing in PsyCap development is not just good for employees' wellbeing; it's also essential if organizations want enough competent staff to deliver excellent care now and in the future. And when healthcare professionals are seen as dynamic individuals who can build psychological resources, there is hope for resilience and better retention in difficult circumstances— and a better experience for patients too.

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# CHAPTER 2

**Algorithmic Governance in the  
Age of Artificial Intelligence:  
Public Administration, Democratic  
Legitimacy and Accountability**

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## 1. Introduction

Public administration is the field in which decisions concerning society's common problems are made, public resources are distributed, and individuals' rights and obligations take concrete form. For this reason, the technical tools used in public institutions have a different significance from efficiency tools used in private companies. An error in a company's customer recommendation system and an error in a system that determines eligibility for social assistance do not produce the same consequences. In the first case, the consumer experience may be adversely affected, whereas in the second, a family's access to basic income support, a child's ability to benefit from protective services, or the likelihood that a person will be subject to law-enforcement scrutiny may be affected. Therefore, the introduction of artificial intelligence into public administration should be considered not merely as a technical innovation, but as an issue concerning how power is exercised.

Today, artificial intelligence is used in public institutions and organizations to forecast service demand, process and categorize large datasets, prioritize citizen applications in the public interest, and enable effective, efficient and sound state-citizen communication. While algorithms are used in the public sector across a broad range of areas such as facial recognition systems, decision-support operations and resource allocation, their capacity to accelerate processes, reduce costs and contribute to consistency in services is noteworthy. In addition, issues such as coordination among public institutions, data quality, accountability, privacy and explainability are regarded as factors that may constrain or limit the technical efficiency that algorithms can provide (Ahn & Chen, 2022; Wirtz et al., 2019; Zuiderwijk et al., 2021).

At the core of the problem lies the assumption that algorithms are neutral and inherently objective tools. Yet what an algorithm measures, the data on which it is trained, which errors it considers acceptable, which threshold value it uses, and what outcome it defines as success are connected to pre-existing political and administrative choices. A model does not merely reflect social reality; it reconstructs that reality through particular categories, risks and priorities. Therefore, algorithmic decision-making does not mean that decisions are not made by humans. In many cases, the decision is moved to an earlier stage: the selection of data, the definition of the target variable, model design, the procurement contract, or the determination of the weight that the implementing public official will give to the algorithmic recommendation (Kitchin, 2017; Selbst et al., 2019; Yeung, 2018).

Within this framework, the central question of the chapter is as follows: What does algorithmic decision-making in public administration mean for democratic legitimacy and accountability in the age of artificial intelligence? Three sub-

questions are addressed in order to answer this question. First, in what ways does artificial intelligence transform the capacity, organizational form and policy processes of the state? Second, how does the transition from governance to algorithmic governance affect the exercise of public authority and public values? Third, what institutional arrangements are needed for algorithmic decisions to be legitimate, explainable and accountable?

The purpose of this chapter is not to examine all the technical features of artificial intelligence technologies in detail. The main focus here is on data-driven systems used in public decision-making processes that produce direct consequences for individuals. High-impact decisions are particularly important in this respect. This is because such decisions can directly affect whether a person can benefit from a public service, their economic situation, their freedom, their access to education and health services, or their position in society. Areas such as social assistance, social services, child protection, law-enforcement activities, justice, health, education, migration and public-sector employment may be considered within this scope. For this reason, it is not sufficient to measure the success of algorithmic systems used in these areas solely in terms of predictive accuracy. Equality, due process, the ability to provide reasons for the decision, the availability of effective avenues of objection, the preservation of human oversight, and the clear determination of where responsibility lies are at least as important as technical success (Busuioc, 2021; Green, 2022; Haeri et al., 2022).

## **2. Artificial Intelligence and the Transformation of the State**

### **2.1. The Importance of Artificial Intelligence in Public Administration**

Artificial intelligence is not a structure consisting of a single program code, but a broad technological field that uses different computational methods and brings together various forms of application. In terms of the use of artificial intelligence in public administration, machine learning, pattern recognition, natural language processing models, predictions based on statistical analysis, classification algorithms and decision-support systems are particularly important. These systems can infer relationships within large datasets in order to address a particular problem concerning the public or public administration, classify a new application according to predetermined criteria, or estimate the probability of an event occurring through statistical analysis methods. Through these applications, a recommendation supporting a public official's decision may sometimes be provided; applications may sometimes be ranked according to the necessary criteria to produce a priority score; and, in some cases, a process may be directly automated through a natural language processing model (Desouza et al., 2020; Madan & Ashok, 2023; van Noordt & Tangi, 2023).

The significance of artificial intelligence for public administration varies according to the area in which it is used. While the use of artificial intelligence in areas such as archiving or the storage of meteorological data keeps its impact on

citizens and administrative processes relatively limited, its use in areas such as decision-making and the exercise of authority in public governance increases this impact. If the same institution uses artificial intelligence to decide whether a person should be classified as risky, ineligible, fraudulent or in need of protection, the system becomes part of administrative discretion and of the relationship between the administration and the citizen. For this reason, three questions are important when evaluating the use of artificial intelligence: Which decision does the system affect? Whose rights and opportunities does the decision change? Can the system's output be challenged? (Haeri et al., 2022; Sun & Medaglia, 2019).

## **2.2. Reconstructing State Capacity Around Data and Models**

In traditional public administration, decision-making capacity is largely based on legal rules, organizational hierarchy, the professional knowledge of personnel and record systems. With artificial intelligence, this capacity will be supported by datasets, computational infrastructure, model-development capabilities and continuous performance monitoring. State capacity will be assessed not only in terms of how many personnel are employed or how much budget is available, but also in terms of what data are produced, the extent to which these data can be integrated, and how model outputs are linked to public purposes (Madan & Ashok, 2023; van Noordt & Tangi, 2023).

This situation is also changing the state's relationship with private companies. When the technical capacity of public institutions is limited, algorithm development, data processing or cloud services may be outsourced to private contractors. Such outsourcing may facilitate public services' access to technology; however, it may also make a significant part of public authority dependent on contracts, licensing conditions and the contractor's closed technical infrastructure. Although the public institution continues to bear legal responsibility for a decision made with the support of artificial intelligence, it may not fully know how the model operates. The problem that arises is not limited to technical opacity, commonly described as the "black box." It also concerns how responsibility for the decision is distributed among the institution, the public official, the software developer of the artificial intelligence application used, and the data provider that supplies the data used in making the decision (Busuioc, 2021; Desouza et al., 2020; Raji et al., 2020).

## **2.3. Transformation of the Public Policy Cycle**

Artificial intelligence is not used only at the implementation stage of public policy. Data analytics can affect the visibility of problems, the prioritization of agendas and the comparison of policy options. A public institution may use algorithmic analysis to decide which applications will be classified as "urgent," which areas will be inspected, or which groups will be considered to have a high need for services. Thus, problem definition, which is the starting point of the

policy process, may be shaped by indicators produced by technical models (Hofisi & Lamidi, 2026; Valle-Cruz et al., 2020).

Valle-Cruz and colleagues address the public policy cycle in the age of artificial intelligence through a dynamic framework encompassing agenda setting, policy formulation, implementation and evaluation. This approach shows that artificial intelligence is not used at one stage of the policy process independently of the others. A model produces data during policy implementation; these data are used to train a new predictive system; the new predictive system affects resource allocation; and the results of that allocation return as performance indicators in the next evaluation. In this way, the policy cycle turns into a feedback regime in which human decisions and model outputs mutually reinforce one another (Valle-Cruz et al., 2020).

**2.4. Possibilities and Limits of Transformation**

The potential contributions of artificial intelligence to public administration can be grouped under three headings. First, it can increase processing capacity. While manually processing large and complex datasets takes time, algorithmic systems can classify large numbers of records in a short period. Second, it has the potential to increase consistency in policy implementation. Evaluating applications with similar conditions in a similar way may reduce the risk of arbitrary differences between individuals. Third, it can provide forecasting and early-warning capacity. In areas such as health, disaster management, transportation or public safety, resources may be planned in advance (Desouza et al., 2020; Wirtz et al., 2019).

The table below presents together the principal administrative promises of transformation through artificial intelligence and the governance questions that accompany them.

**Table 1**

| Area of transformation            | Expected administrative contribution                  | Main governance question                                                                      |
|-----------------------------------|-------------------------------------------------------|-----------------------------------------------------------------------------------------------|
| Prediction and early warning      | Advance planning of resources and faster intervention | Who bears the cost of prediction error, and in which groups are errors concentrated?          |
| Classification and prioritization | Faster processing of applications                     | Which categories are used, and how do these categories make citizens visible or invisible?    |
| Decision support                  | Staff making informed decisions                       | Does the human decision maker have the authority and capacity to question the recommendation? |

| <b>Area of transformation</b>            | <b>Expected administrative contribution</b> | <b>Main governance question</b>                                                                            |
|------------------------------------------|---------------------------------------------|------------------------------------------------------------------------------------------------------------|
| Automated eligibility or risk assessment | Reduction of transaction costs and delays   | Can the citizen access the reasons for the decision and effectively challenge it?                          |
| Natural language processing and chatbots | Facilitation of communication with citizens | Does the system include users with different languages, disabilities and socioeconomic conditions equally? |
| Oversight and fraud detection            | Protection of public resources              | How will losses of rights suffered by individuals due to false positives be remedied?                      |

### **3. From Governance to Algorithmic Governance: Conceptual and Theoretical Framework**

#### **3.1. Transition from Governance to Algorithmic Governance**

The concept of governance refers to a form of administration in which public affairs are not determined solely by state hierarchies, and in which public institutions, private enterprises, civil society organizations, experts and citizens participate in decision-making processes at different levels. Within this framework, the state is conceived not so much as the sole decision maker, but as an actor that brings different actors together, sets the rules and coordinates public purposes. Governance does not mean that hierarchy disappears; it shows that hierarchy becomes intertwined with networks, contracts, expertise and information flows (Robles & Mallinson, 2023; Wilson, 2022).

Algorithmic governance emerges when computational capacity is added to this multi-actor and information-intensive structure. The concept refers to the use of algorithms in public service delivery, decision-making, policy implementation, risk management and processes of behavioral steering. However, algorithmic governance is not simply the use of algorithms by public institutions. Algorithms assume an administrative role to the extent that they affect what information will be collected, what behavior will be regarded as a risk, which application will be prioritized and which action requires intervention (Kitchin, 2017; Yeung, 2018).

Yeung conceptualizes algorithmic regulation as the continuous collection of data from a dynamic environment, the production of computational knowledge from those data, and the monitoring, steering or modification of behavior in order to achieve a predetermined objective. Within this framework, algorithmic regulation does not emerge only at the final stage of decision-making. The setting of standards, the collection of data and the application of sanctions or the

achievement of behavioral change are parts of the same system. This distinction is important for public administration because the political effect of an algorithm begins not only when it makes the “final decision,” but at the moment when it determines the preconditions of that decision (Yeung, 2018).

### **3.2. Socio-Technical Approach**

Treating algorithmic systems solely as technical objects is insufficient to explain their effects in public administration. A model does not consist only of a dataset and software code. It is part of a socio-technical order that operates together with the institution’s objectives, the implementation practices of public personnel, legal limitations, procurement relationships and citizens’ reactions. For this reason, Chen and colleagues argue that artificial intelligence systems should be examined as an interaction between technical and social elements (Chen et al., 2023; Selbst et al., 2019).

The socio-technical approach offers a way of thinking that prevents responsibility from being transferred to “the algorithm.” If a model produces discriminatory outcomes, the explanation that “the algorithm calculated it this way” is not sufficient. It is necessary to ask on what data the model was trained, how the objective function was selected, which threshold value the institution adopted, how the public official used the output, and how the citizen’s objection was evaluated. Each of these questions makes visible different actors and institutional stages within the decision chain (Raji et al., 2020; Rakova et al., 2021).

### **3.3. Theoretical Dimensions of Legitimacy**

Legitimacy is not limited to whether a decision taken by a public authority complies with the law. It also requires the decision to be regarded as acceptable, fair and reasoned by the society affected by it. According to Suchman, legitimacy is considered in three dimensions: pragmatic, moral and cognitive. Pragmatic legitimacy is based on the perception that the decision is useful or acceptable in terms of the interests of the relevant parties. Cognitive legitimacy, in turn, is based on the decision and the reasons underlying it being understandable and capable of being regarded as natural by society. Finally, moral legitimacy concerns whether the decision is regarded as appropriate, right and fair in terms of social norms and public values (Suchman, 1995).

Grimmelikhuijsen and Meijer examine the legitimacy of algorithmic decision-making through input, process and output dimensions. Input legitimacy refers to the relationship of the decision-making process with democratic participation and political oversight; process legitimacy refers to the procedural and legal conditions of the decision; and output legitimacy refers to the compatibility of decisions with public values and citizens’ expectations. This distinction prevents

algorithmic systems from being evaluated solely on the basis of outcome accuracy (Grimmelikhuijsen & Meijer, 2022; Hillo et al., 2026).

The framework below presents the legitimacy of an algorithmic decision together with accountability mechanisms.

**Table 2**

| Legitimacy         | Main question                                                            | Algorithmic risk                                                            | Institutional safeguards                                                              |
|--------------------|--------------------------------------------------------------------------|-----------------------------------------------------------------------------|---------------------------------------------------------------------------------------|
| Input legitimacy   | Who determines the objectives, criteria and priorities?                  | Technical experts or suppliers effectively determining public purposes      | Political oversight, public consultation, clear definition of purpose and scope       |
| Process legitimacy | Through what procedure and on what grounds is the decision produced?     | Black-box model, data error, unexplained classification                     | Notification, statement of reasons, audit trail, independent review, human assessment |
| Output legitimacy  | Is the decision fair, equitable and consistent with the public interest? | Discriminatory error, exclusion, false positive, loss of access to services | Discrimination testing, impact assessment, objection, remedy, periodic monitoring     |

### 3.4. Theoretical Dimensions of Accountability

Accountability is not the same as responsibility. While responsibility indicates to whom a duty or outcome belongs, accountability describes the process through which the actor in question is required to provide information before a forum, offer explanations, justify actions and, when necessary, face consequences. Bovens defines accountability as a relationship between an actor and a forum; he emphasizes the actor’s obligation to explain and justify actions, the forum’s authority to ask questions and pass judgment, and the possibility that the actor may face consequences (Bovens, 2007).

Busuioc examines problems of algorithmic accountability through the provision of information, the giving of explanations and possible consequences. It is not sufficient for public institutions merely to disclose that an algorithm is used in decision-making processes. Institutions should provide meaningful information explaining the purpose of the artificial intelligence system, the data sources it will use in decision-making processes, the system’s limitations, patterns of error and the role played by humans in the decision-making process. It should also be clear how the model output produced by the artificial intelligence system will be interpreted by the public institution, how an incorrect decision will be identified and how that decision will be corrected. Accountability is not

limited to a model being technically explainable; the explanation provided must be understandable and usable by individuals in society, public oversight bodies and courts (Busuioc, 2021; Diakopoulos, 2016).

## **4. Artificial Intelligence and Algorithmic Decision-Making in Public Administration**

### **4.1. Types of Algorithmic Decisions and the Decision Chain**

Algorithmic decision-making in public administration takes place at different levels of intensity. At the first level, the algorithm organizes information or produces recommendations for staff review. At the second level, the system prioritizes applications and directs the public official's attention to particular files. At the third level, the algorithm places the individual in a risk or eligibility category, and the decision made by a human is shaped to a large extent by this score. At the fourth and final level, to the extent permitted by law, an administrative act may be established or rejected automatically. Accordingly, each level of algorithmic decision-making requires different legal and administrative safeguards (Haeri et al., 2022; Veale et al., 2018).

It is not sufficient to evaluate the algorithmic decision-making process only through the final administrative act that emerges. This is because the decision is, in fact, formed at the end of several interconnected stages. At the first stage of the process, the necessary data are collected, classified and matched with different records. It is precisely at this point that many problems begin. Which personal data are used, whether those data are up to date, how incomplete records are completed, and by what method information held by different institutions is brought together can directly affect the nature of the subsequent decision (Veale et al., 2018).

At the second stage, what the model is intended to measure is determined. Administrative concepts such as risk, need, success or irregularity are converted at this stage into quantifiable indicators. The model is then run and produces a score, classification or recommendation. Yet the process does not end there. The result produced is subsequently converted into a concrete action by a public official or an automated system. At the final stage, the decision is communicated to the relevant person, any objection is received, and the action is reassessed or corrected if necessary.

### **4.2. Bureaucratic Form and Administrative Discretion**

Bureaucracy consists not only of rules and hierarchy, but also of areas of administrative discretion. When street-level public officials apply general rules to concrete cases, they consider the circumstances of the person receiving the service, the urgency of the application and the flexibility permitted by law. Artificial intelligence may narrow these areas of discretion in some cases, while in others it may create new forms of discretion. Which data the model regards as

meaningful, whether the public official follows the algorithmic recommendation, and the authority to recognize exceptions constitute new forms of discretion (Bullock et al., 2020; Green, 2022).

Bullock, Young and Wang show that the relationship between artificial intelligence and bureaucratic form is not linear and that the effect of artificial intelligence on administrative discretion varies according to organizational structure. Artificial intelligence may accelerate the transition from street-level and screen-level bureaucracies to system-level bureaucracy. In such a case, decision-making may shift from the slow and detailed evaluation of individual files toward administration through large datasets and standardized classifications (Bullock et al., 2020).

For human oversight to be effective, relations of authority within the institution are important. If a public official is continuously penalized when departing from the algorithm's recommendation, or if performance indicators are based on conformity with the model, the actual decision may have been left to the algorithm even if the law requires a human decision. By contrast, if the public official can question the model output, evaluate alternative evidence and justify a different decision, the algorithmic system can be kept within the limits of decision support (Alon-Barkat & Busuioc, 2023; Green, 2022).

#### **4.3. Automation Bias and Selective Adherence**

The presence of a human element in artificial intelligence applications does not mean that human error disappears automatically. The evidence does not support a strong generalization about automation bias; a more specific concern is selective adherence to algorithmic advice when it aligns with group stereotypes. Alon-Barkat and Busuioc describe automation bias in public decisions as excessive adherence to algorithmic advice even when other warning signs are present, and define selective adherence as the tendency to adopt the advice when it aligns with group stereotypes (Alon-Barkat & Busuioc, 2023).

Experimental studies conducted in the Netherlands did not find general evidence of excessive adherence to algorithmic advice in every case; instead, they showed that tendencies toward selective adherence could become stronger when the advice aligned with group stereotypes. In a study conducted with public officials, this pattern was found to weaken after a public scandal that produced discriminatory outcomes. This finding is important in two respects. First, it shows that public personnel do not always follow algorithmic recommendations blindly. Second, it indicates that institutional experience and awareness of discrimination can change human-algorithm interactions (Alon-Barkat & Busuioc, 2023).

#### **4.4. Explainability, Transparency and Trust**

Transparency is used in two different senses in algorithmic systems employed in decision-making processes. The first refers to individuals' access to information about the system. Transparency in this sense may be necessary for ensuring institutional transparency; however, it may not be sufficient for a citizen to understand a concrete decision. The second meaning is the understandable explanation of why a particular decision was produced by the algorithmic system used in the decision-making process. If an institution discloses the name of the algorithmic model used, the data categories used in the decision-making process and the general operating logic of the system, but does not explain why a particular individual was denied a particular service, the problem of procedural fairness remains (de Bruijn et al., 2022; Grimmelikhuijsen, 2023).

Grimmelikhuijsen examines the perceived trustworthiness of automated decisions made by an algorithmic system by distinguishing the transparency of the algorithmic model used in the decision-making process into the dimensions of accessibility and explainability. According to Grimmelikhuijsen's study, access to information about an algorithmic system and the explainability of the decisions produced by that system have different effects on trust. The findings suggest that access to information alone is insufficient; understandable explanations of individual decisions may matter more for trust, although the strength of this effect varies by context. The explanation provided in the study affects not only trust in the system but, to some extent, trust in the human decision maker as well. Nevertheless, the effects of transparency vary according to the context of the decision (Grimmelikhuijsen, 2023).

#### **4.5. Algorithmic Bias and Discrimination**

Algorithmic bias may arise when a model produces different error rates for different social groups, reproduces inequalities inherited from the past, or systematically places particular groups at a disadvantage. The problem here is not always that the data are "wrong." Even if data have been collected correctly in technical terms, they may carry traces of discriminatory practices from the past. Moreover, even if the model does not directly use a protected characteristic, it may produce a similar discriminatory effect through indirect variables such as neighborhood, level of education, income, language or health data. The system may appear neutral, yet may not be neutral in its outcomes (Mittelstadt et al., 2016; Vetrò et al., 2021; Wachter et al., 2021).

Anti-discrimination oversight should not be regarded as a one-time check either. Data distributions, social conditions and institutional uses change over time. A model that initially produces balanced results may not show the same performance in another region or on a population with different characteristics. Therefore, particularly in high-impact algorithmic systems, periodic audits should be conducted, changes made to the model should be recorded, and clear

rules should exist that allow use of the system to be suspended when serious deviations arise (Raji et al., 2020; Vetrò et al., 2021).

#### **4.6. Diffusion of Responsibility and Supplier Relationships**

When an algorithmic decision made using an artificial intelligence system is produced with the participation of multiple actors, responsibility may become dispersed. The institution providing the data used in the decision-making process, the company developing the artificial intelligence model, the public institution purchasing the system for use, the public official using the purchased model and the citizen affected by the decision produced by the system occupy different points in the same chain. None of these actors may be able to control the entire process alone. However, the fragmented nature of control should not be interpreted as meaning that responsibility disappears (Busuioc, 2021; Raji et al., 2020; Rakova et al., 2021).

A public institution that purchases an externally developed system for use in making particular decisions cannot transfer to the supplier from which it purchased the system the legal and democratic accountability arising from decisions produced by that system. The supplier that develops or sells the system should inform the public institution about the technical operation, data quality, model performance and known limitations of the purchased artificial intelligence system. Contracts should ensure the auditability of the model used in decision-making, its ability to be tested independently, the maintenance of event logs, and the possibility of stopping the system when necessary. When a citizen affected by a decision concerning fundamental rights and freedoms requests information about the operation of the system, the necessary information should not be withheld on the grounds of trade secrecy (Busuioc, 2021; Iunes Monteiro, 2025).

### **5. The Democratic Dimension and Legitimacy of Algorithmic Governance**

#### **5.1. Algorithmic Conditions of Democratic Legitimacy**

Democratic legitimacy cannot be reduced to the merely formal association of public decisions with actors who hold office through elections. Citizens should be able to influence the formation of decisions, decisions should be subject to legal and procedural safeguards, and outcomes should be compatible with equality and the public interest. Algorithmic systems can affect all three dimensions at the same time. The purpose of a model may not be determined through elections; the operation of the model may be closed to citizen participation; and the outcomes may systematically place particular groups at a disadvantage (Grimmelikhuijsen & Meijer, 2022; Hillo et al., 2026; Mišić et al., 2025).

From the perspective of input legitimacy, the first question is which public problem the algorithm is designed to solve. Objectives such as “detecting risky applications,” “reducing irregularities” or “targeting services” may appear technical, but they contain normative choices. The institution decides which risk is important and which error is acceptable. For example, it may be possible to identify more irregularities by flagging more people as suspicious; however, in that case more innocent people will be subject to scrutiny and access to services may become more difficult. Defining the objective is a political decision that begins before the algorithm is coded (Wilson, 2022).

## **5.2. Process Legitimacy: Procedural Fairness and Explanation**

The legitimacy of the decision-making process concerns how the decision is produced, independently of the outcome of the decision. When citizens are notified of a decision made against them, they want to know which data were used to reach that decision, the criteria on which the decision was based, and, in cases where a human element is present in the decision-making process, who made the decision. Even if the outcome of the decision does not change, a fair procedure can affect the acceptability of the decision. The fundamental elements of procedural fairness in algorithmic decision-making systems are notification of the decision, provision of reasons for the decision, the citizen’s right to be heard, the right to challenge the decision, and human oversight (Grimmelikhuijsen & Meijer, 2022; Veale et al., 2018).

## **5.3. Output Legitimacy: Equality, Public Interest and Trust**

Output legitimacy concerns the effects that algorithmic decisions produce in society. Success in public administration is not merely the rapid delivery of a service. A decision should be compatible with values such as equality, social justice, privacy, security, autonomy and human dignity. The systematic review by Chen and colleagues emphasizes that public values should be addressed within a broad framework in artificial intelligence governance and that stakeholder participation should be increased (Chen et al., 2023; Mišić et al., 2025).

In the experimental study conducted by Hillo, Vento and Erkkilä with public managers and citizens in Finland, algorithmic transparency and human discretion were found to increase perceived legitimacy in the context of automated decision-making. The effects were stronger among public managers; this shows that the legitimacy of algorithmic governance is related not only to the perceptions of service users, but also to the attitudes of public personnel who design and implement decision-making processes (Hillo et al., 2026).

## **5.4. Technical Expertise, Democratic Oversight and Power Relations**

Algorithmic governance increases the weight of technical expertise in public decisions. Experts and suppliers with technical knowledge play an important role in the creation of the model. Although this expertise is necessary, it should not

replace democratic authority. What the model should optimize, which value should be prioritized and which risks are acceptable cannot be resolved entirely through technical questions alone. These decisions are political and normative in nature (Jobin et al., 2019; Morley et al., 2020).

Democratic oversight does not consist merely of making all of an algorithm's code public. Oversight bodies should be able to examine the model's purpose, legal basis, data sources, performance across groups, the points at which human intervention occurs, and records of errors and objections. Legislative bodies should address algorithmic systems during budgetary and policy oversight; ombudsmen, data protection authorities and public audit institutions should possess the necessary expertise. Courts should be able to examine the legal basis of automated or algorithmic decisions and whether effective avenues of redress are available (Busuioc, 2021; Diakopoulos, 2016; Iunes Monteiro, 2025).

### **5.5. An Accountability Architecture**

Accountability, one of the most important elements of algorithmic public administration, cannot be guaranteed by a single report prepared on decisions taken and actions implemented, or merely by the existence of an ethics board to which complaints can be submitted. An accountability architecture should cover all stages of the decision-making process. At the first of these stages, before the system is put into use, its purpose, possible risks, the legal basis of the decision-making process and, where applicable, alternative methods should be evaluated. The quality of the data used in decision-making and the performance of the algorithmic model should be monitored regularly throughout the use of the system. All changes deemed necessary in the system should be recorded together with their reasons, and unexpected effects caused by decisions should be reported. After a decision is made using an artificial intelligence system, the reasons for the decision should be explained to the relevant citizen and avenues of objection should be provided where necessary. If an error is identified after the decision is communicated to the citizen, the decision should be corrected and, to the extent appropriate, the resulting harm should be remedied (Bovens, 2007; Busuioc, 2021; Raji et al., 2020).

Bovens's democratic, constitutional and learning-based evaluation perspectives can be applied together to artificial intelligence-supported algorithmic decision-making systems. While the democratic perspective questions whether algorithmic decision-making systems are open to the oversight of citizens affected by the decisions and of elected bodies, the constitutional perspective focuses on whether the system is based on legal authority, respects fundamental rights and provides procedural safeguards. The learning-based perspective examines whether public institutions using artificial intelligence algorithms generate knowledge and experience from errors that arise and whether they develop mechanisms to correct the system when necessary (Bovens, 2007).

When these perspectives are considered together, accountability can be seen not to be limited to punishing actors responsible for an incorrect decision; it also includes correcting errors in the decision-making process and developing institutional learning. Although determining who is responsible for an incorrect algorithmic decision is important, punishing only a public official does not resolve structural problems in the data on which the decision is based or in the design of the algorithmic model. Therefore, the public institution in which the incorrect decision was made should document the error, ensure that the harm suffered by the affected citizen is remedied or compensated, and implement the institutional and technical changes necessary to prevent similar errors from recurring (Bovens, 2007).

## **6. The Future of Public Administration: From the Decision-Making State to the Decision-Making Algorithm**

The expression “decision-making algorithm” creates the impression in public administration that decision-making authority is transferred from humans to a technical structure.

Although this assessment appears striking at first glance, it has certain limitations in explaining the position of algorithms within public administration. It is not correct to regard algorithmic systems as independent actors that determine public purposes, establish political priorities or exercise legal authority on their own. An algorithm does not decide by itself which public service should be prioritized, which social group needs more support, or to which areas limited public resources should be allocated. Such choices fall directly within the sphere of political and administrative responsibility. The nature of the result an algorithm will produce depends largely on which data are supplied to the system, how those data are classified, which variables gain weight in the decision-making process and which threshold values are used. Thus, behind the operation of algorithmic systems there are always people, institutions and, in a broader sense, a particular administrative order. Nevertheless, this does not mean that algorithms have no effect on decision-making processes. Which applications a system flags as risky, which problems it makes a priority, or which data it brings before the decision maker may, over time, affect the attention of public officials and the working practices of institutions. For this reason, the power of algorithmic systems often derives not from making decisions directly, but from shaping the informational environment in which the decision is made and the options from which it is selected (Kitchin, 2017; Yeung, 2018).

Different forms of development concerning the future of public administration can be identified. The first is a structure in which algorithmic systems are used primarily as technical tools that accelerate administrative processes and reduce transaction costs. In this type of application, the objectives of the public institution, its duties based on legislation and its decision criteria remain

unchanged; the algorithm mainly contributes to carrying out the existing process in less time, with less human labor and in a more orderly manner. For example, classifying large numbers of applications, grouping similar files, identifying missing documents or carrying out routine procedures automatically may be considered within this scope. Here, the role of the algorithm within the administrative system is limited, and its principal function is to support a process defined by humans. However, as the area of application expands, situations arise in which the algorithm no longer remains merely a technical assistant but becomes part of the process of preparing decisions (Hofisi & Lamidi, 2026; Wirtz et al., 2019).

At this point, a hybrid structure in which humans and algorithms work together emerges as a more realistic model. In the hybrid model, rather than replacing the public official, the algorithmic system increases the official's capacity to process information. Algorithms can make important contributions especially in operations such as examining large datasets in a short period, comparing different options, identifying unusual situations or detecting particular risk patterns. Responsibility for the final decision, however, remains with the public official. It is not sufficient for this merely to be stated in legislation. If the employee is constantly required to explain themselves when making a decision contrary to the system's recommendation, or if the institution's performance criteria reward compliance with algorithmic recommendations, the decision-making authority that appears to remain with the human may, over time, effectively come under the direction of the algorithm. The sound operation of the hybrid model is therefore closely related to public personnel having the professional capacity to understand model outputs, question them when necessary, and make a different decision (Alon-Barkat & Busuioc, 2023; Green, 2022).

At a more advanced stage, it is possible to speak of a structure in which algorithmic systems cease to be tools used only for particular operations and become embedded in the institution's general decision architecture. In this approach, which may be called institutional algorithmic governance, the issue is no longer only how accurately a piece of software produces results. How data are collected, the purpose for which the model is developed, the administrative processes in which its output is used, the extent to which the public official can intervene in that output, and the means through which the citizen can challenge the decision taken are addressed within the same institutional framework. Such a structure neither accepts the algorithm as an independent administrator nor regards it merely as an ineffective and neutral technical tool. The algorithm is an element of the institutional order in which the decision is produced. For this reason, technical design cannot be separated from legal and administrative responsibility (Hofisi & Lamidi, 2026; Mišić et al., 2025).

For this reason, the understanding of performance in algorithmic public administration should also be reconsidered. Speed and cost savings are undoubtedly important for public services; however, the success of public administration cannot be measured solely by how quickly procedures are completed. The extent to which incorrect decisions can be corrected, how citizens' objections are resolved, whether systematic inequalities emerge among different social groups, and whether the reasons for decisions are explainable should also form part of institutional performance. Taking these criteria into account makes it possible to consider the use of artificial intelligence not merely as a tool of technical efficiency, but within the framework of legality, accountability and public legitimacy. In this way, the use of algorithmic systems in public administration can be understood not as the elimination of human decision-making, but as an administrative transformation in which the distribution of duties and responsibilities between humans and technology is redefined (Chen et al., 2023; Mišić et al., 2025).

## **7. Conclusion and Recommendations**

The introduction of artificial intelligence into public administration is significantly transforming the state's decision-making capacity and the organization of public services. Artificial intelligence can facilitate the processing of large datasets, the forecasting of service demand, the classification of applications and the prioritization of resources. However, these possibilities do not automatically strengthen the democratic and legal character of public decisions. On the contrary, the incorporation of data, models and supplier relationships into decision-making processes requires the restructuring of legitimacy, equality, explainability and accountability (Hofisi & Lamidi, 2026; Zuiderwijk et al., 2021).

Algorithmic legitimacy should be assessed by jointly examining how objectives are determined, the procedures through which decisions are produced, and whether outcomes align with equality and the public interest (Grimmelikhuisen & Meijer, 2022).

First, at the input level, the objectives that the algorithm seeks to achieve and the criteria it uses in making assessments should be subject to political oversight. These cannot be secrets determined behind closed doors; the public should be allowed to discuss them openly, and all stakeholders affected by these decisions should be able to participate in the process and express their views (Wilson, 2022).

There are certain conditions that must be met in decisions made using artificial intelligence. The first of these is that the process should have clear rules. This is because significant problems may arise if the procedural stages in algorithmic decision-making processes are not structured correctly. Therefore, all rights of citizens arising from law should be incorporated into the algorithmic system as

fundamental elements of a fair and procedurally proper decision-making process, and no compromise should be made in this regard. In order to protect the rights of individuals, the following conditions should be included in the system: (Busuioc, 2021; Green, 2022; Iunes Monteiro, 2025).

a- A decision concerning an individual should be communicated to the individual concerned,

b- When necessary, the actions carried out during the decision-making process and how the process operates should be explained,

c- If the individual wishes, they should be able to challenge the decision,

d- When the individual requests it, they should be able to ask for the decision to be reviewed by a human,

By incorporating these rights into the system, the individual can be better protected against incorrect decisions made by artificial intelligence systems or decisions that may adversely affect their rights.

Before a decision or decisions made by artificial intelligence systems acquire official status, during the formation of the decision and after the output has been produced, there are two important reviews that should be carried out. The first is an examination of whether the algorithm has a structure compatible with the principle of equality and whether it contains any code or data that could lead to discrimination. This review should be repeated after every change made to the system. Finally, after the decision is produced, it should be subject to human review, and the person carrying out this review should be given legal responsibility for evaluating the decision (Green, 2022; Vetrò et al., 2021; Wachter et al., 2021).

Artificial intelligence decision-making systems need to have an effective accountability structure. The first step is to determine the answer to the question, “Who should be accountable to whom?” Systems or structures should be established that can question the institution or public official responsible for explaining the decision made by the decision-making mechanism and, when necessary, impose sanctions. In other words, the party responsible for reviewing and explaining the decision and the institutions that will compel that party to account for harms that may arise from the decision should be clearly identified (Bovens, 2007; Busuioc, 2021).

This is because the institution using algorithmic structures in decision-making processes and the public official responsible for reviewing and explaining those decisions cannot avoid responsibility merely by stating that the decision was made by the algorithm and claiming that the responsible party is the artificial intelligence system or the supplier that produced the system. The supplier that produces and sells the system should also have responsibilities. These

responsibilities should include informing the public institution about the limitations of the developed system and providing the public official who will review the decision with the information necessary to question the reliability of that decision (Busuioc, 2021; Raji et al., 2020).

Within the framework of the requirements stated above, there are five basic recommendations that should be implemented as a priority at the institutional level. The first is that if an algorithm is to be used in a system that will seriously affect citizens' rights and their ordinary access to public services, it should never be put directly into operation. First, a comprehensive assessment should be completed by examining in detail what kinds of effects the algorithmic system will produce on the existing public system, and the next stage should not be entered unless this assessment produces a positive result (Iunes Monteiro, 2025; Raji et al., 2020).

This assessment cannot be a merely symbolic document; it should cover the legal basis of the system, its concrete areas of use, all available alternative solutions where necessary, all data sources required for the system to operate, all possible biases in the system regardless of whether they produce positive or negative effects, error rates arising across different groups when the system is used, and, where necessary, a supporting objection mechanism (Iunes Monteiro, 2025; Morley et al., 2020).

The impact assessment should not be merely an internal document serving only the institution's own purposes. Not all findings obtained from the impact assessment should be treated as internal documents, because such documents can be accessed only by employees of the relevant public institution. Instead, all parts of the assessment findings should be made public, except for personal data and exceptional commercial information that must be protected as trade secrets (Iunes Monteiro, 2025; Wilson, 2022).

In addition, all public institutions that use artificial intelligence systems in decision-making processes should prepare a list of the algorithmic systems and artificial intelligence systems they use. The information on this list should be kept up to date, and the list should be renewed when necessary. All information that is required to be included should be recorded fully and accurately (Raji et al., 2020; Rakova et al., 2021).

The list should state the purpose for which each decision-making system is used and the area of public service in which it operates. It should also explain the extent to which the system influences the formation of decisions. Information should be provided about the categories of data used during the operation of the system and the company from which the system was purchased. In addition, it should be stated whether the artificial intelligence-supported decision-making system requires human oversight and, if so, at which stages of the system this oversight is carried out. The list should also include when the system was last

audited and how many objections have been made to the results it has produced to date.

Third, every individual affected by an algorithmic decision should be provided by the public institution with an explanation of the decision that they can genuinely understand, and practical and usable channels of objection should be established so that they are not deprived of the opportunity to protect their rights. The explanation provided to the individual cannot consist merely of placing the algorithm's technical code before them; ordinary people cannot be expected to understand such complex code, and such an approach does not serve the purpose of explanation. A genuinely useful explanation should clearly set out, in a manner understandable even to people without technical knowledge, which basic personal data were used in the concrete individual decision and which fundamental criteria were followed in carrying out the assessment. If, after examining the explanation, the individual determines that incorrect data were used in their case, they should have the right to request correction of those inaccurate data. If they believe that the algorithmic model has misclassified their situation—for example, if they have been placed in a category of restriction that is not appropriate to them—they should also have the right to object and request re-verification. They should also be able to request that an independent reviewer with no conflict of interest in the matter completely re-examine the outcome of the decision. Furthermore, the period granted to the individual for objection should not become unusable in practice because they cannot access adequate information about the objection process or do not have the means to submit an objection through online digital channels. It should be ensured that even people with limited ability to use a smartphone and no access to online notifications can successfully submit their objections within the prescribed period and are not deprived of the ability to protect their rights because of technical barriers (de Bruijn et al., 2022; Grimmelikhuijsen, 2023).

Human oversight of systems used in decision-making processes is meaningful only when the public official has the authority to question model outputs, assess alternative evidence and, when necessary, make a different decision. The legal responsibilities of the public official required to perform this duty should be defined, and their powers should be determined by law. This personnel should receive the necessary training and be trained to examine the results of the system. The public official should be able to question the decision when necessary and ensure that it is reassessed. When serious problems are identified in the operation of the system, the official should request suspension of the system or have the authority to suspend it. A professional protection mechanism should be established to ensure that personnel who request a change to the conclusion reached by the algorithm, or who cause the system to be run again in order to reassess the algorithmic result, are not held liable or penalized. In addition, a decision by personnel that departs from the algorithm's recommendation should

not arbitrarily be classified as an automation error. Where necessary, such a decision should be accepted as a reasonable outcome arising from adequate public assessment, because humans can take into account real-life circumstances that algorithms cannot encompass and can make assessments that are more consistent with the public interest (Green, 2022; Iunes Monteiro, 2025).

Fifth, governance activities should involve all relevant stakeholders in the process and should be sustained over the long term. Unlike many tasks that end when they are completed, the sound governance and operation of algorithms require continuous attention and cannot be left solely to the state. All stakeholders related to the algorithm should be included in the process so that they can contribute at different stages. These stakeholders include public officials who use the algorithm, service recipients who depend on the algorithm to access public services, independent oversight bodies with no ties to any interested party, researchers, professional organizations that apply professional standards, grassroots civil society groups, and suppliers that develop and sell the algorithm. All parties participate in the governance process at different stages of the life cycle extending from the introduction of the algorithm into use to its continuous operation (Morley et al., 2020; Rakova et al., 2021).

Finally, the public administration of the future will neither return to the old model based entirely on human decisions nor transfer all decision-making authority unconditionally to algorithms. Many people focus on the false dichotomy of whether decisions in the future will be made entirely by humans or entirely by machines. In reality, neither of these two extremes will occur. What lies ahead is a hybrid governance model in which humans and algorithmic systems work together, and in which humans and machines can make better decisions together by drawing on their respective strengths (Hillo et al., 2026; Wuttke et al., 2026).

Whether this model is democratic depends less on the technical sophistication of the algorithm than on certain fundamental questions: What objectives is the algorithm designed to achieve? Who oversees its operation? How are citizens informed about the logic of decision-making? How are errors corrected? No matter how advanced an algorithm's technology may be, if it is used for the wrong purposes, operates without oversight, ordinary people cannot understand why it made a particular decision about them, and errors are left uncorrected, the model cannot be described as democratic (Hofisi & Lamidi, 2026; Wuttke et al., 2026).

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