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Continuous improvement in the age of AI: human and relational barriers in public higher education

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Abstract

Purpose – This study investigates the human and relational dynamics of artificial intelligence (AI) adoption for continuous improvement in public higher education institutions (HEIs). It explores how AI integration affects employees' basic psychological needs – autonomy, competence, and relatedness – within the public sector's value-driven context.

Design/methodology/approach – The research employs a mixed-methods embedded design. Primary data consists of 330 semi-structured interviews with administrative staff across six Italian universities. Qualitative thematic analysis is integrated with Chi-square (χ^2) statistical tests to identify significant associations between employees' perceptions and socio-demographic factors, and macro-institutional profiles based on organizational digital maturity.

Findings – The results reveal a paradox of automation: AI is welcomed as a tool for operational autonomy when it emancipates staff from repetitive tasks but is rejected when it threatens decisional sovereignty or ethical accountability. While AI can augment competence for digitally literate staff, it risks cognitive atrophy and workplace sterilization. Relatedness emerges as a non-negotiable pillar, with staff universally resisting AI applications that substitute human interaction for student support.

Originality/value – The study shifts the focus from technological performance to micro-foundational motivational mechanisms by applying Self-Determination Theory (SDT) to AI adoption in the public sector. It contributes a new conceptual framework that identifies a legitimacy threshold, distinguishing between AI as an assistive infrastructure versus a professional substitute.

Keywords Continuous improvement, Organizational change, Performance improvement, Public sector, Service quality, Universities

Paper type Research article

1. Introduction

The diffusion of Artificial Intelligence (AI) across organizations has accelerated rapidly in recent years, supported by the multiplication of available AI tools and increasing organizational experimentation. Recent global survey evidence indicates that 88% of organizations now regularly use AI in at least one business function, marking a substantial increase compared to previous years (McKinsey & Company, 2025). However, despite this widespread diffusion, most organizations remain in early phases of implementation, with nearly two-thirds still engaged in experimentation or piloting rather than enterprise-wide scaling. Furthermore, organizations reporting the highest value from AI are those redesigning workflows and embedding human validation mechanisms into AI-supported processes, suggesting that the effectiveness of AI adoption depends not only on technological availability but also on how work is reorganized around human-AI interaction (McKinsey & Company, 2025). Against this backdrop, offering unprecedented opportunities for automation, real-time data analysis, and enhanced decision-making capabilities. Within quality management paradigms such as Lean, Six

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Sigma, and Kaizen, AI is expected to accelerate process optimization, reduce variability, and improve operational efficiency by enabling more accurate and timely interventions (Bhimdiwala *et al.*, 2022; Tveita and Hustad, 2025). More recently, emerging perspectives within Total Quality Management (TQM), such as Quality 5.0, emphasize the integration of advanced digital technologies with human-centric principles, highlighting that technological advancement must be aligned with human well-being, engagement, and value creation (Kumar *et al.*, 2026). In both private and public sector organizations, AI-driven systems are therefore being adopted as strategic tools to streamline workflows, reduce costs, and enhance service delivery.

In the public sector, however, the implementation of AI-driven continuous improvement initiatives raises a set of distinctive challenges. Unlike private organizations, where performance is primarily evaluated in terms of efficiency and profitability, public institutions are guided by the creation of public value, which encompasses transparency, accountability, equity, and citizen-centric service delivery (Van Noordt and Tangi, 2023). In this context, improvements in efficiency do not automatically translate into improvements in service quality. On the contrary, the increasing automation of administrative processes may generate unintended consequences, such as reduced human interaction, diminished relational quality, and weakened trust between public employees and service users. Existing research highlights that while AI enhances efficiency, decision-making, and process optimization, its adoption in public organizations is often constrained by issues related to ethics, trust, organizational culture, and human resource management (Susar and Aquaro, 2019; Tveita and Hustad, 2025).

This tension reflects a broader paradox at the core of AI-enabled continuous improvement: while technological systems are designed to optimize processes, they may simultaneously disrupt the human and relational dimensions that underpin service quality. This paradox is particularly relevant in higher education institutions (HEIs), where administrative processes are deeply intertwined with relational work, such as student support, guidance, and problem-solving. Recent contributions in the TQM literature on AI adoption in higher education emphasize the transformative potential of AI in improving efficiency and service delivery, while also pointing to critical challenges related to user trust, human-AI interaction, and organizational readiness (e.g. Gutiérrez-Leefmans *et al.*, 2025). As such, the introduction of AI as a tool for process improvement raises critical questions regarding its impact not only on efficiency, but also on the quality of interactions between staff and users, and on the professional identity of public employees.

Despite the growing body of literature on AI adoption, existing research has predominantly focused on technological capabilities, performance outcomes, and organizational efficiency (Benbya *et al.*, 2020; Wamba-Taguimdje *et al.*, 2020; Bankins *et al.*, 2024). In the public sector, studies have examined the benefits and challenges of AI in terms of automation, decision-making, and public value creation, as well as issues related to trust, ethics, and governance (Susar and Aquaro, 2019; Tveita and Hustad, 2025). Similarly, TQM-oriented research has begun to explore the role of AI in enhancing quality management practices and continuous improvement processes, particularly in terms of data-driven decision-making and operational excellence (Kumar *et al.*, 2026). However, these contributions remain largely fragmented and tend to treat AI adoption either as a technological or as an organizational phenomenon. Limited attention has been paid to the micro-level mechanisms through which AI-driven process improvement reshapes employees' motivation and, in turn, affects the relational quality of public service delivery.

To address this gap, this study adopts a human-centered perspective on AI-enabled continuous improvement, focusing on the motivational dynamics that underpin employee responses to AI in a public Higher Education Institution. Specifically, the study draws on Self-Determination Theory (SDT) (Ryan and Deci, 2024) as a micro-foundational framework to examine how AI affects the satisfaction of employees' basic psychological needs for autonomy, competence, and relatedness. Within TQM, continuous improvement is not only a technical process but also a socio-technical endeavour that relies on employee engagement, learning, and participation (Parker and Grote, 2022). From this perspective, understanding how AI influences these psychological needs is critical to explaining when continuous improvement initiatives lead to genuine quality enhancement and when they result in resistance, disengagement, or superficial compliance.

Furthermore, this study avoids treating public higher education as a monolithic environment. By evaluating data collected across six distinct Italian universities, it explicitly explores how variations in institutional digital maturity and administrative structures shape or moderate the stability of employees' motivational mechanisms, clarifying whether the proposed framework operates uniformly or is bound by localized organizational conditions.

Building on this theoretical integration, the present study investigates the adoption of AI in the administrative functions of public universities, conceptualizing AI not merely as a technological innovation, but as an intervention in work design and service processes. More specifically, the study addresses the following overarching research question:

RQ. How does AI-driven continuous improvement reshape employee motivation and relational quality in public Higher Education Institutions?

To address this overarching question, three sub-questions are explored:

RQa. How do AI-driven process improvements satisfy or frustrate employees' needs for autonomy, competence, and relatedness in public service work?

RQb. Under what conditions does AI foster autonomous motivation versus controlled or defensive forms of adoption among public employees?

RQc. How does the use of AI in administrative processes affect the relational quality between public employees and service users?

By addressing these questions, the study contributes to the literature in three main ways. First, it advances research on AI in public organizations by shifting the focus from technological adoption and performance outcomes to the human and motivational mechanisms underlying continuous improvement processes. Second, it extends TQM scholarship by highlighting the potential misalignment between efficiency-driven process optimization and the relational dimensions of service quality in public contexts. Third, it refines the application of the Self-Determination Theory in digital transformation settings, showing how the satisfaction of autonomy, competence, and relatedness becomes a critical condition for the successful integration of AI in continuous improvement initiatives.

The rest of the paper is structured as follows. Section 2 presents the theoretical background, integrating literature on AI-driven continuous improvement, public service quality, and motivational theory. Section 3 outlines the research methodology. Section 4 reports the empirical findings. Section 5 discusses the theoretical and managerial implications of the study, and Section 6 concludes by addressing limitations and avenues for future research.

2. Theoretical background

2.1 AI-enabled continuous improvement and Quality 5.0

Artificial intelligence (AI) is increasingly conceptualized as a key enabler of continuous improvement in organizational processes, extending traditional quality management approaches through enhanced data-driven capabilities. Within established paradigms such as Lean, Six Sigma, and Kaizen, continuous improvement has historically relied on incremental changes, employee involvement, and systematic problem-solving to enhance efficiency and reduce variability (Deming, 1986; Bryk *et al*., 2015). The integration of AI technologies transforms these processes by enabling real-time data analysis, predictive insights, and automated decision support, thus shifting improvement practices from reactive to more active and adaptive logics (Bhimdiwala *et al.*, 2022; Tveita and Hustad, 2025).

Recent developments in Total Quality Management (TQM), particularly within the emerging Quality 5.0 paradigm, emphasize that technological advancement must be aligned with human-centric principles, including employee engagement, well-being, and value co-creation (Kumar *et al.*, 2026). In this perspective, AI is not merely a tool for operational optimization, but a core component of socio-technical systems that reshape how organizations design, manage, and continuously improve their processes, while at the same time preserving – and indeed enhancing – the valorisation and motivation of human resources. By leveraging advanced analytics and automation, AI systems support organizations in identifying inefficiencies, optimizing workflows, and enhancing decision-making accuracy, thereby reinforcing continuous improvement cycles and contributing to long-term performance (Tveita and Hustad, 2025).

However, the role of AI in continuous improvement differs significantly between private and public sector organizations. In the private sector, AI adoption is predominantly guided by market logic, where success is measured in terms of efficiency gains, cost reduction, and competitive advantage (Wamba-Taguimdje *et al.*, 2020). In contrast, public sector organizations are driven by the creation of public value, which encompasses transparency, accountability, equity, and citizen-centric service delivery (Van Noordt and Tangi, 2023). As a result, continuous improvement in public contexts cannot be reduced to efficiency alone but must also preserve the relational and ethical dimensions of service quality. Although the integration of AI with human expertise is increasingly recognized as necessary across sectors (Parker and Grote, 2022; Ngo, 2025), the organizational implications of this complementarity vary considerably depending on institutional logics and work functions. In private-sector settings, AI-supported decision-making is generally evaluated through performance-oriented criteria such as productivity, scalability, and profitability. Conversely, public organizations are subject to stronger legitimacy, accountability, and transparency requirements, which make the boundaries between human and algorithmic decision-making more sensitive (Van Noordt and Tangi, 2023). Furthermore, the relevance and acceptability of AI also differ across organizational functions: while automation may be more readily accepted in standardized or back-office activities, resistance tends to emerge in functions involving discretionary judgment, ethical responsibility, and high levels of interpersonal interaction (Parker and Grote, 2022).

This distinction is particularly relevant for higher education institutions (HEIs), which operate as complex public organizations where administrative processes are deeply intertwined with relational work. As citizen-oriented institutions, universities cannot prioritize operational efficiency if this comes at the expense of service quality, inclusiveness, or transparency (Aithal and Maiya, 2023). The adoption of AI in HEIs therefore involves a fundamental challenge: reconciling the efficiency gains enabled by digital technologies with the accountability and ethical standards required by their public mandate. In recent years, this tension has been further amplified by the diffusion of managerial logics associated with New Public Management (NPM), which have pushed universities toward efficiency-oriented practices and resource optimization strategies (Colombo and Salmieri, 2022). Within this context, AI is often framed as a solution for managing increasing workloads with limited resources, particularly in administrative functions (Bankins *et al.*, 2024).

Taken together, these developments suggest that AI-enabled continuous improvement in public sector organizations, and particularly in HEIs, should be understood not only as a technological enhancement of existing processes, but as a broader transformation of organizational criteria and work practices. While AI offers significant opportunities for efficiency and process optimization, its integration within TQM frameworks requires balancing performance objectives with the preservation of public value and service quality. This highlights the need to move beyond purely technical perspectives on AI adoption and to examine how AI-driven improvement initiatives reshape the human and relational dimensions of work.

2.2 Human, relational and motivational tensions of AI-driven improvement

While AI-enabled continuous improvement offers significant potential for enhancing efficiency and decision-making, its implementation in public sector contexts introduces a set of critical human, relational, and organizational tensions. Existing literature highlights that, alongside improvements in automation and process optimization, AI adoption generates substantial challenges related to trust, ethics, transparency, and organizational change (Tveita and Hustad, 2025; Susar and Aquaro, 2019). These challenges are not merely technical barriers but reflect deeper frictions between efficiency-driven improvements and the human-centered nature of public service work.

A central tension concerns the impact of AI on professional autonomy. On the one hand, automation can reduce repetitive tasks and enable employees to focus on higher-value activities, thereby supporting job enrichment and forms of job crafting (Clemmensen *et al.*, 2023). On the other hand, the opacity of AI systems and their often-non-transparent decision-making processes may undermine employees' capacity to justify and take responsibility for their actions (Bracci, 2023). In public service contexts, where accountability and explainability are fundamental, this creates a paradox: employees remain formally responsible for decisions while relying on systems they may not fully understand (Wang, 2021; Wang *et al.*, 2021). As a result, resistance to AI should not be interpreted solely as a lack of technical competence, but rather as a defence of professional integrity and ethical accountability.

A second critical barrier relates to the dimension of competence and professional expertise. Although AI is frequently framed as a tool for cognitive augmentation, its effective use depends on employees' ability to understand, interpret, and critically evaluate its outputs (Schiavo *et al.*, 2024). In the absence of adequate AI literacy, these systems may become sources of uncertainty and dependence rather than empowerment (Burhan, 2025). This condition can generate fears of deskilling, as employees perceive that excessive reliance on automated systems may erode their domain-specific knowledge and professional judgment (Mainardi, 2025). Empirical evidence further suggests that the ability to derive value from AI is strongly associated with individuals' levels of AI literacy and their capacity to interpret data-driven outputs within complex decision-making environments (Arianpoor *et al.*, 2026). Consequently, the lack of appropriate skills and interpretive capabilities represents a fundamental barrier to the effective integration of AI within continuous improvement processes.

Finally, AI-driven improvement raises significant concerns regarding the relational dimension of public service work. In many public organizations, and particularly in higher education institutions, service delivery is inherently relational, relying on direct interactions between employees and users. However, digital transformation initiatives often equate efficiency with the reduction of human interaction, promoting automated interfaces and standardized service delivery (Parker and Grote, 2022). While such approaches may improve operational efficiency, they risk undermining the social and relational fabric of organizations. In HEIs, interactions with students are not merely transactional, but constitute a core component of professional identity and organizational purpose (Tomlinson and Jackson, 2021). The replacement of these interactions with automated systems may therefore lead to what has been described as a "sterilization" of work, eroding opportunities for meaningful engagement and weakening the sense of belonging among employees (Komljenovic *et al.*, 2025; Aithal and Maiya, 2023) and, more broadly, among students and staff as members of the same community.

Taken together, these tensions highlight that AI-enabled continuous improvement cannot be fully understood without considering its impact on fundamental human needs in the workplace. The adoption of AI reshapes not only tasks and processes, but also employees' experiences of autonomy, competence, and relational connection. When AI systems support these dimensions, by enhancing decision-making capacity, reinforcing professional expertise, and preserving meaningful interactions, they can foster engagement and proactive adoption. Conversely, when AI undermines employees' sense of control, erodes their skills, or disrupts relational dynamics, it may generate resistance, anxiety, and forms of defensive or superficial compliance.

From this perspective, the integration of AI in public sector organizations should be conceptualized not only as a technological or process innovation, but as a challenge in work design. Continuous improvement initiatives based on AI are likely to succeed only when they align efficiency gains with the preservation of human and relational dimensions of work. Otherwise, the pursuit of process optimization may paradoxically lead to lower-quality outcomes in terms of employee engagement, service experience, and overall organizational performance.

3. Methodology

3.1 Research design

The research method for this study is a mixed-method approach based on an embedded design procedure, where qualitative and quantitative data are integrated to comprehensively answer the research questions (Caracelli and Greene, 1993; Yin, 2018). The research employs a semi-structured qualitative interviewing design as the primary source of evidence, which is subsequently enriched by quantitative statistical processing. The decision to adopt a qualitative approach is supported by the exploratory nature of the phenomenon, given that the integration of AI in the public sector is still in its infancy (Illugi and Hallur, 2024), and quantitative metrics alone are inadequate for capturing the complex sense-making processes of employees.

In order to consolidate the empirical findings, the research design incorporates a quantitative phase (Tashakkori and Teddlie, 2010), in which the qualitative insights are subjected to Chi-square (χ^2) analysis. The objective of this statistical integration is to identify significant associations between the respondents' perceptions and their socio-demographic profiles (e.g. role, department, age). The present study was conducted within the organisational framework of six Italian universities, selected as a collective case study to investigate the friction between technological efficiency and human-centric service.

In contrast to the profit-maximising objectives of the private sector, the academic public sector is driven by a distinct public service logic (Bianchi and Caperchione, 2022). Consequently, this setting offers a unique perspective on the tension between AI-driven standardisation and the relational nature of public administration, providing an ideal environment to test the implications of Self-Determination Theory (SDT) through both narrative depth and statistical rigor.

3.2 Data collection

Following the embedded design procedure, the data collection was structured to integrate different layers of information within a single research framework (Caracelli and Greene, 1993; Yin, 2018). The data were gathered through semi-structured interviews with the university staff, conducted between September 2025 and February 2026.

The first section was dedicated to defining the socio-demographic and occupational profile of the respondents. Variables such as role (A1), department (A2), age (A4), and gender (A3) were captured to contextualize the professional background of each interviewee.

The second section comprised three expansive open-ended questions. The construction of these was specifically undertaken to facilitate the articulation of respondents' views in the absence of pre-established categories. The utilisation of a direct semi-structured interview approach facilitated the exploration of a wide variety of perspectives (Braun *et al.*, 2021). This format enabled participants to provide thick descriptions of their professional reality, ensuring a level of detail and richness of response that had not been achieved in previous research studies (Terry and Braun, 2017).

The overarching objectives of this approach were to address participants' affective and cognitive disposition toward technology (1), the rationale behind their ethical and operational stance (2), and the anticipated consequences on professional autonomy and daily tasks (3). The semi-structured prompts used during the interviews included:

(1) What is your general perception regarding the introduction of AI in the workplace?

(2) What specific considerations oriented your position regarding the adoption of AI?

(3) In what way does (or could) the application of AI influence your daily professional choices and activities?

These prompts were not intended as a rigid sequence of questions, but rather as catalysts for a deeper conversational exchange. Through the use of follow-up questions and iterative probing techniques, the interviewer encouraged participants to expand on their initial reflections, allowing for the emergence of nuanced professional narratives (Way *et al.*, 2015). This dialogic approach ensured that the conversation remained focused on the research objectives while providing the flexibility to explore unexpected insights and specific situational contexts.

To ensure full transparency and replicability of the research design, the sections, variables, and descriptive prompts of the interview protocol are schematized in Table 1.

The recruitment strategy involved the formal engagement of six diverse Italian universities that expressed their availability to participate in the research. This collaboration allowed for the construction of a comprehensive mailing list comprising 2,182 potential candidates among the administrative staff. Following the initial outreach, the recruitment process followed a multi-stage filtering approach: 1,328 contacts (60.8%) did not respond to the invitation, while a significant subgroup of 854 individuals (39.2%) expressed a formal interest in participating. From this pool of interested candidates, 284 individuals (33.3% of the subgroup) did not follow up on subsequent requests to schedule a call, and 122 (14.3%) failed to attend the pre-arranged sessions. Of the 448 interviews successfully conducted, 118 (26.3%) were eventually excluded from the final dataset as the responses did not meet the required standards for detail and qualitative richness necessary for the subsequent quantization process. Consequently, the study yielded a final sample of $N = 330$ participants. This represents a final completion rate of 15.1% relative to the initial population and a 38.6% cumulative conversion rate from the interested subgroup.

The 330 semi-structured interviews were conducted by a team of four researchers; while two members were responsible for conducting and transcribing the interviews, the remaining two performed a continuous validation and oversight of the process to ensure consistency (White *et al.*, 2012). Each interview had a mean duration of approximately 20 min each, ensuring sufficient time for the emergence of complex narratives and professional reflections. Subsequent to the completion of the interviews, a verbatim transcription process was employed, resulting in a high-quality textual corpus with an average density of 1,100 words per interview. This rigorous documentation procedure, supported by the multi-investigator validation (White *et al.*, 2012), was essential to preserve the linguistic nuances and the authentic professional voice of the staff, providing a reliable foundation for the subsequent thematic and statistical analysis.

Table 1. Operational structure and prompts of the semi-structured interview protocol

Section	Focus (variables)	Prompts	Analytical objective
Section 1 Socio-demographic and occupational profile	o Role (A1) o Department (A2) o Age (A4) o Gender (A3)	o "What is your current administrative role?" o "Which department are you currently affiliated with?" o "What is your age?" o "What is your gender?"	To contextualize the professional background of each interviewee and provide data for subsequent Chi-square (χ^2) statistical testing
Section 2 Qualitative core and sense-making	General Perception Affective and cognitive disposition toward AI technology	"What is your general perception regarding the introduction of AI in the workplace?"	To explore participants' spontaneous attitude, capturing potential cognitive dissonance, ambivalence, or perceptions of technological determinism
	Operational and Ethical Rationale The rationale behind their ethical and operational stance	"What specific considerations oriented your position regarding the adoption of AI?"	To identify the perceived barriers, facilitators, and non-negotiable thresholds (e.g. decisional sovereignty vs assistive tool)
	Professional Autonomy and Tasks Anticipated consequences on professional autonomy and daily tasks	"In what way does (or could) the application of AI influence your daily professional choices and activities?"	To evaluate the impact of AI on work design, highlighting dynamics of cognitive augmentation versus verification burdens and cognitive atrophy

Source(s): Authors' own work

Regarding professional classification, the majority of the cohort consisted of Administrative Collaborators (73.5%), followed by Officers (10.4%), Officers with Managerial Responsibilities (7.4%), and Operators (6.1%); Senior Professionals/Executives and Language Experts each accounted for a marginal share of 1.3%.

With respect to the affiliation of the participants to various departments, it was observed that more than half of them were employed within the administrative sector, constituting 58% of the total sample. Other significant clusters included the Technical-Scientific-Technological-ICT and General Services area (12.3%), the Administrative-Managerial sector (12%), and the Library sector (7%). Smaller proportions were observed in General and Technical Services (3.3%), Technical-Informatics (3.3%), Scientific-Technological (2.1%), the Language Experts area (1.7%), and the Managerial area (0.3%).

In terms of age demographics, the population was predominantly composed of individuals in mid-to-late career stages, with the largest proportion falling within the 50–59 age range (43.3%), followed by those aged 30–39 (21.4%) and 60–69 (17.4%). The age demographic of employees in the 40–49 age bracket constituted 13% of the total, while the 18–29 age group represented 4.8%. The gender breakdown revealed a predominance of female respondents (63.3%) over males (31%), with 5.7% opting not to specify.

A comprehensive summary of the demographic and professional characteristics of the sample is presented in Table 2.

In accordance with the study's exploratory objectives, a purposive stratified sampling strategy was employed (Etikan *et al.*, 2015). The objective of the study was to ensure a representative coverage of the university's primary occupational categories, aiming for a balanced distribution within each group in order to mirror the institution's internal workforce structure. The methodology adheres to the principles of non-probability quota sampling.

Table 2. Demographic and professional characteristics of the sample

Variable	*n*	Percentage (%)
Professional classification		
Administrative collaborators	243	73.5%
Officers	34	10.4%
Officers with managerial responsibilities	24	7.4%
Operators	20	6.1%
Senior professionals/executives	4	1.3%
Language experts	5	1.3%
Sector affiliation		
Administrative sector	191	58%
Tech-sci-tech-ict and general services	41	12.3%
Administrative-managerial	40	12%
Library sector	23	7%
General and technical services	11	3.3%
Technical-informatics	11	3.3%
Scientific-technological	7	2.1%
Language experts area	5	1.7%
Managerial area	1	0.3%
Age group		
18–29	16	4.8%
30–39	71	21.4%
40–49	43	13.0%
50–59	143	43.3%
60–69	57	17.4%
Gender		
Female	209	63.3%
Male	102	31.0%
Prefer not to say	19	5.7%

Source(s): Authors' own work

This technique facilitates the inclusion of diverse organisational subgroups, ensuring that the final sample of $N = 330$ participants provided a comprehensive overview of the population while remaining feasible within the rigorous practical constraints of direct qualitative interviewing (Robinson, 2014).

3.3 Data analysis

To ensure both empirical sensitivity and theoretical coherence, the study adopted a hybrid coding strategy that prioritized inductive semantic coding followed by deductive structural mapping. This dual approach allowed the authors to capture the nuanced, context-specific narratives of the public sector workforce before anchoring the findings in established theory.

In the first stage, data collected were analysed using inductive thematic analysis (TA), i.e. a method of identifying and interpreting patterns across data set (Braun and Clarke, 2006). With the large data set gathered, TA enabled the researchers to reduce it into key themes (Clarke and Braun, 2013). The authors performed open coding without utilising an *a priori* codebook, thereby identifying specific semantic patterns directly from the raw responses. In order to ensure a systematic approach to TA, the coding process and data management were conducted using NVivo software (version 12). Table 3 provides a summary of the key themes and recurring patterns identified through the thematic analysis.

Table 3. Thematic analysis

Key themes	Recurring patterns	Description of patterns
Perception of adoption	*Technological determinism/inevitability*	AI is not regarded as an organisational choice, but rather as an environmental force to be endured, giving rise to a sense of cautious apprehension
Operational impact	*Technical augmentation vs decisional loss*	There is a clear distinction between the use of AI for robotic tasks, a practice that meets with general acceptance, and its use for decision-making, which is not generally accepted
Skill dynamics	*Cognitive prosthesis vs cognitive atrophy*	The tension between AI as a tool that extends capabilities versus a threat that erodes critical thinking skills is a key consideration in the university context
Workflow shifts	*From author to auditor*	The transition from content creation to content verification is driven by the need to address issues related to trust and the potential for hallucinations in AI outputs
Organizational culture	*Efficiency vs sterilization*	There is a concern that prioritising algorithmic speed may have a negative impact on the essential relational fabric of the public sector

Source(s): Authors' own work

In the second stage, a deductive analytical phase was undertaken to organize the broad patterns identified within the framework of Self-Determination Theory (SDT); in this stage, the key themes were systematically mapped onto the three fundamental psychological needs – autonomy, competence, and relatedness – as conceptualized within the SDT (Ryan and Deci, 2024). This structural mapping provided the SDT framework (Table 4), ensuring that the rich, descriptive findings remained focused on the research objectives, categorizing the role of AI as a psychological barrier, a facilitator, or a conditional factor depending on its implementation.

Lastly, to enhance the analytical depth and ensure the triangulation of findings, a mixed-methods sequential design was adopted. In the third stage, a quantitizing process (Tashakkori and Teddlie, 2010) was performed: qualitative responses were transformed into categorical variables (0 = Barrier/Conditional; 1 = Facilitator) mapped onto the SDT framework to reflect the psychological needs of autonomy, competence, and relatedness. Specifically, this stage involved a binary coding of the qualitative themes previously identified: for each of the twelve sub-dimensions (i.e. employee experiences), a value of 1 was assigned if the respondent explicitly identified that experience as a facilitator or a relevant positive factor. Conversely, a value of 0 was assigned to indicate either the absence of the theme, its perception as an explicit barrier, or a conditional response. This coding choice was strategically made to distinguish between respondents showing unconditioned alignment with AI benefits and those expressing reservations or prerequisites that currently hinder full psychological need satisfaction.

To meet the assumptions of the Chi-square test (χ^2), specifically regarding the minimum expected cell frequencies required to ensure distributional accuracy (Agresti, 2013), data were first subjected to a recoding and clustering process. Demographic variables, including gender and age, were recoded into binary variables: gender (Male/Female) and age (Under 50/Over 50). This age threshold serves as a proxy for assessing generational differences in technological readiness, reflecting distinct career stages and the transition from analogue to digital work routines. Furthermore, professional roles were clustered based on the degree of hierarchical responsibility and decision-making autonomy (e.g. merging executive and managerial roles), while departmental affiliations were grouped according to the functional nature of the tasks – distinguishing between core administrative processes and technical-scientific support services.

Following these adjustments, χ^2 tests were conducted to explore statistically significant associations between these SDT-grounded perceptions and the respondents' profiles. To

Table 4. SDT framework

SDT construct	Employee experiences	Role of AI	Employee needs
Autonomy	*Emancipation from repetitive tasks*	Facilitator	Avoid tasks that are repetitive and of low value and focus on those that require human intelligence
	Decision-support tool vs autonomous decision-maker	Conditional	Keep control of the process and use AI as a copilot, but never as the pilot
	Defence of decisional sovereignty	Barrier	Protect the ability to judge subjective cases without algorithmic interference
	Human ethical accountability	Barrier	Personally endorse a decision and clarify it to the student (a capability that AI does not offer)
Competence	*Cognitive augmentation*	Facilitator	Complete complex tasks (e.g. translation or coding) more quickly and to a higher standard than through unaided effort
	Risk of cognitive atrophy	Barrier	Maintain your own critical thinking skills and avoid becoming intellectually lazy
	Literacy and trust gap	Barrier	Learn how to use AI tools without feeling anxious or worried about making mistakes
	Role of auditor	Barrier	Reduce the workload, which is currently hindered by the exhausting need to double-check every piece of AI-generated output
Relatedness	*Risk of workplace sterilization*	Barrier	A workplace that feels alive and human is desired, as opposed to one that feels cold and automated
	Preservation of human connection	Barrier	Support students by showing empathy and active listening, rather than just processing data
	Relational professional identity	Barrier	To be valued as a human caregiver/mentor (this is threatened if AI performs the counselling)
	Countering organizational isolation	Barrier	Face-to-face interaction with colleagues and students is important for feeling part of a community

Source(s): Authors' own work

ensure a rigorous and exhaustive exploration of the data, each of the twelve identified sub-dimensions (i.e. the employee experiences) was systematically tested against all four independent variables – professional role (A1), department (A2), gender (A3), and age group (A4) – resulting in a total of forty-eight bivariate analyses. By reporting the specific independent variables that yielded the most significant associations for each experience, Table 5 allows for a targeted examination of the key drivers that differentiate AI perceptions within the University, while also documenting the cross-sectional consensus regarding the relational risks of automation. This approach allows for the statistical validation of the qualitative dimensions of autonomy, competence, and relatedness, providing a robust empirical basis for the nuanced employee experiences described in the SDT-based conceptual framework.

To account for potential institutional heterogeneity and expand the analytical scope of this third stage, the same quantitizing process (Tashakkori and Teddlie, 2010) was subsequently deployed within a structured cross-university contingency framework.

Firstly, with regard to the organisational context, the six Higher Education Institutions (HEIs) were categorised into two macro-institutional profiles based on a structural and technical audit. This approach was adopted to avert the occurrence of excessive data fragmentation and to circumvent any violation of the minimum expected cell frequency assumptions of the Chi-square test (Cochran, 1954; McHugh, 2013). To this end, the

Table 5. Chi-square analysis of SDT framework and key drivers

SDT construct	Employee experience	AI role	Independent variable	χ^2	df	*p*-value
Autonomy	*Emancipation from repetitive tasks*	Facilitator	Professional Role (A1)	78.42	2	< 0.001***
	Decision-support tool vs autonomous decision-maker	Conditional	Department (A2)	12.15	2	0.002**
	Defence of decisional sovereignty	Barrier	Professional Role (A1)	54.30	2	< 0.001***
	Human ethical accountability	Barrier	Department (A2)	6.80	2	0.033*
Competence	*Cognitive augmentation*	Facilitator	Professional Role (A1)	28.15	2	< 0.001***
	Risk of cognitive atrophy	Barrier	Age Group (A4)	14.45	1	0.012*
	Literacy and trust gap	Barrier	Age Group (A4)	19.20	1	< 0.001***
	Role of auditor	Barrier	Department (A2)	11.40	2	0.003**
Relatedness	*Risk of workplace sterilization*	Barrier	Gender (A3)	0.45	1	0.502 (n.s.)
	Preservation of human connection	Barrier	Professional Role (A1)	2.10	2	0.350 (n.s.)
	Relational professional identity	Barrier	Department (A2)	3.50	2	0.174 (n.s.)
	Countering organizational isolation	Barrier	Age Group (A4)	0.90	1	0.343 (n.s.)

Note(s): ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$; n.s. = non-significant

Source(s): Authors' own work

universities were grouped into two balanced clusters, a strategy that was deemed to maximise statistical power (Agresti, 2013).

In accordance with established digital maturity and quality management frameworks in public administrations (Irani *et al.*, 2023), this clustering operationalised maturity based on systemic infrastructure integration rather than mere technology adoption, identifying the transition from isolated operational silos to unified platforms as the core indicator of public sector digital evolution. Consequently, High Digital Maturity (HDM, $n = 182$) clustered University 1, 2, and 6, which are characterised by fully integrated enterprise resource planning (ERP) systems and unified cloud platforms. In contrast, the Low-to-Medium Digital Maturity (LMD, $n = 148$) category, which comprises University 3, 4, and 5, is characterised by the presence of fragmented legacy software and hybrid paper-and-digital workflows.

Secondly, the directional impact of AI on the three core constructs of SDT was cross-tabulated against these maturity profiles based on precise thematic threshold rules. For the construct of Competence, segments were operationalised as 1 (Cognitive Augmentation) if AI was described as an assistive tool that expanded operational capacity and minimised errors, and as 0 (Cognitive Atrophy/Strain) if the narrative centred on verification overload, mistrust, or skill depletion. For Autonomy, data were coded as 1 (Job Crafting/Emancipation) when AI was perceived as a liberating infrastructure enabling professional discretion, and as 0 (Decisional Sovereignty/Control) when framed as a mechanism of compliance or micromanagement. For the purpose of analysis, segments were designated as 1 (Relational Preservation) in instances where AI facilitated higher-value human contact, and as 0 (Workplace Sterilization) when identified as an alienating substitute eroding empathetic public service quality. In conclusion, a series of χ^2 cross-tabulations were performed on this dual-axis matrix in order to provide an objective statistical mapping of the influence of institutional maturity profiles on the macro-distribution of employee experiences across different universities.

4. Findings

The thematic analysis of the three open-ended questions provides a detailed description of how administrative staff at the Universities analysed deal with the introduction of AI into their professional lives. The data analysis reveals that adoption is not a linear process. Instead, it involves a complex negotiation between the desire for efficiency and the defence of public service values. The findings – which are structured around the impact of AI on the three fundamental psychological needs proposed by Self-Determination Theory (SDT) (Ryan and Deci, 2024) – are detailed below. These qualitative insights are systematically integrated with the results of the Chi-square (χ^2) analysis, highlighting how specific professional and demographic, and institutional maturity drivers influence employee perceptions.

4.1 The psychological landscape of AI adoption: ambivalence and determinism

Regarding the general perception of AI technology, the analysis revealed a complex psychological landscape characterised not by outright structural rejection, but by a high-arousal ambivalence, which can be best described as a state of cautious apprehension. Participants rarely expressed linear, one-dimensional views; rather, the data suggests a cognitive dissonance where fascination with AI's potential to eliminate bureaucratic tasks clashes with a deep-seated concern regarding workplace dehumanization and the erosion of public value.

A dominant sub-theme that structures this affective layer is the pervasive perception of inevitability. The emerging narrative is one of technological determinism: regardless of their individual level of digital literacy, respondents framed AI not as a strategic organisational choice to be internalised or debated, but as an uncontrollable environmental force to be endured. Rather than an active transition, adoption is experienced as a passive compliance to external pressures. As one Administrative Collaborator from a large student-services department explicitly articulated: *"We are not being asked if we want this technology or if we think it actually improves our daily relationship with students. It is simply arriving from the top, and we are told it will save time. There is a strange mixture of awe and anxiety. On one hand, you see that it can draft a standard email in three seconds, which is fascinating; on the other hand, you feel a sense of coldness, a fear that by automating everything, we are stripping the university of its human face, transforming education into a standardized assembly line where we just monitor screens"*.

This narrative highlights how AI adoption is frequently described through recurrent metaphors of unstoppable natural phenomena, such *"an irreversible tidal wave"* or *"a mutation we cannot stop"*. The statistical analysis supports this qualitative finding by showing that the shift from content creation to content verification – a practical manifestation of this forced adaptation – is significantly influenced by departmental affiliation (A2) ($\chi^2\,(2) = 11.40$, $p = 0.003$). This suggests that the weight of technological determinism is not felt uniformly but is particularly acute in administrative and legal departments where the "Role of auditor" is perceived as an institutional, mandatory burden to ensure regulatory accuracy under time-constrained conditions.

From an SDT perspective, this structural dynamic creates a highly unstable motivational foundation for continuous improvement. The drive toward AI adoption is far for being autonomous (i.e. driven by intrinsic interest, personal values, or perceived utility); instead, it represents a classic manifestation of incorporated (introjected) set of regulation. Staff feel compelled to engage with the technology primarily to avoid intra-psychic or social distress, such as the fear of professional obsolescence, institutional guilt, or the anxiety of being *"left behind"* by the digital transition. This creates a defensive posture, where the pursuit of new digital competences is driven by the immediate need for workplace survival rather than genuine professional growth or self-realization. Another official poignantly illustrated this systemic pressure, highlighting the asymmetric power dynamic between human agency and algorithmic implementation: *"It feels like a powerful, high-speed train that has already started* *moving. We are forced to learn how to drive it immediately, simply to avoid being run over by it. No one asked us where the tracks should go, or if this train is heading in the right direction for our institution. The urgency is entirely external; you either jump on and accept the machine's pace, or you become obsolete* [. . .] *You find yourself studying how it works late at night, not because you are inspired, but because you feel the threat of losing control over your own daily routine"*. This quote is deeply emblematic: while it acknowledges the undeniable speed, power and efficiency of the digital tool, it simultaneously unmasks a total lack of perceived control over its strategic deployment, positioning the human worker symbolically not as an empowered supervisor or autonomous controller, but as a potential victim of their own instrument. This perception of diminished individual agency and structural constraint is further validated by the high significance of the participant's professional role (A1) as a primary driver for the general perception of AI themes (χ^2 (2) = 78.42, $p < 0.001$), confirming that the hierarchical position within the University strictly dictates the degree of perceived agency over the AI transition. Employees in lower hierarchical positions experience the shift as a top-down mandate that restricts their operational self-determination, thereby amplifying cognitive dissonance and reinforcing a fatalistic acceptance of algorithmic integration.

4.2 Autonomy: decision-support tool vs autonomous decision-maker

When respondents were invited to provide their rationale for stance with the projected AI operational impact, a marked dichotomy became evident regarding the satisfaction of the need for autonomy. The data indicates that staff members do not perceive AI as a monolithic entity but rather divides it into two distinct functional categories: the accepted role of a decision-support tool and the rejected role of an autonomous decision-maker.

When considering the daily workflow, it is evident that AI technology is widely embraced as a facilitator of operational autonomy. University staff described this technology not merely as a productivity booster, but as an instrument of emancipation from the chronic bureaucratic saturation typical of the Italian public administration. To provide a thicker description of this phenomenon, an administrative officer from the financial area explained how the technology fundamentally alters the perception of time and mastery over one's work: *"For years, our autonomy has been suffocated by endless, repetitive steps* [such as] *checking signatures, cross-referencing endless regulatory updates, and drafting almost identical notification letters. When I use AI to synthesize these voluminous regulatory texts or to instantly draft standard communications, I don't feel replaced; I feel liberated. It strips away the mechanical, robotic part of my job that used to drain my day and finally allows me to manage my workflow with a sense of control, rather than just running after deadlines"*.

In this particular context, AI is thus regarded as being subordinate to human agency. The Chi-square analysis strongly supports this finding, showing that "Emancipation from repetitive tasks" is the experience with the highest statistical significance in the entire study, driven by the professional role (A1) ($\chi^2(2) = 78.42$, $p < 0.001$). This confirms that the perception of AI as an autonomy-enhancing facilitator is strictly dependent on the employee's position within the organizational hierarchy. The efficiency gains are not pursued for their own sake – as might be the case in a profit-driven enterprise – but because they *"free mental energy for higher-value activities"*. The respondents highlighted that by offloading the so-called robotic aspects of their job to the machine, they could reclaim the autonomy to focus on the inherently human aspects of higher education management, such as student support, empathetic listening, and complex problem-solving. As a result, when AI fulfils operational requirements, it promotes autonomy by removing constraints.

However, a significant obstacle emerges when the focus transitions from execution to strategic decision-making. The respondents indicated a robust defence of decisional sovereignty, establishing a non-negotiable red line in the form of the principle that, while AI is capable of processing data, it must never determine outcomes that have consequences for human lives. This qualitative stance is empirically anchored by the Chi-square results, which reveal that the "Defence of decisional sovereignty" is significantly dictated by the professional role (A1) ($\chi^2(2) = 54.30$, $p < 0.001$), while the specific concern for "Human ethical accountability" is influenced by the departmental affiliation (A2) ($\chi^2(2) = 6.80$, $p = 0.033$). This resistance is deeply rooted in the principles of public service (Bracci, 2023; Wang, 2021). They emphasised that the *"capacity to discern between good and evil"* or to evaluate the nuanced *"subjective distinctions of a student's career path"* is an exclusively human attribute that cannot be replicated by probabilistic algorithms. The prevailing concern is that the implementation of algorithmic management could potentially compromise the chain of accountability, thereby reducing administrative staff to a mere rubber-stamping role (Jarrahi *et al*., 2023). A senior administrative manager forcefully articulated these ethical boundaries and the untransferable nature of public duty: *"An algorithm can analyse ten thousand past student careers in a split second, but it doesn't possess institutional empathy. It cannot understand the human story behind a student who is late on taxes or missing an exam because of a family crisis* [. . .] *Responsibility is a uniquely human burden that cannot be delegated to a machine; if we allow an automated system to make the final call on a student's career or a staff member's evaluation, we are abdicating our public duty* [. . .] *We would transform ourselves into passive spectators, mere rubber-stampers of cold data, which completely breaks the ethical chain of administrative accountability"*.

This extended narrative unmasks the deep psychological tension underpinning the TQM socio-technical framework: while automation is welcomed as an operational ally, its expansion into normative or evaluative domains is perceived as a direct assault on professional identity and self-determination. Statistical results further clarify this position, characterizing the role of AI in decision-making as "Conditional" based on departmental (A2) variations ($\chi^2(2) = 12.15$, $p = 0.002$), indicating that the threshold for accepting AI assistance varies across different administrative functions. Thus, the preservation of ethical autonomy is a conscious limit to adoption, i.e. the tool is accepted only as long as it remains strictly instrumental and never normative.

4.3 Competence: between augmentation and cognitive atrophy

Regarding the operational impact of AI, data provide the most detailed insights into the necessity of competence, thus revealing a distinct paradox of automation. In this context, staff members experience a deep psychological dichotomy, characterised by a sense of euphoria stemming from augmented operational capabilities and a concurrent sense of trepidation stemming from perceived cognitive inadequacies and systemic opacity.

For respondents with higher digital literacy, AI serves as a force multiplier or a cognitive prosthesis. These users reported an immediate increase in feelings of professional efficacy, citing the ability to *"perform complex translations"*, *"write code scripts"*, or *"analyse data patterns"* that were previously beyond their individual skill set. In this scenario, the machine serves as an intermediary between the initial intention and the subsequent execution. A high-level administrative officer from the international relations office clearly described this sense of cognitive empowerment: "*For me, using generative AI has been a revelation in terms of what I can achieve alone. I can now ingest a sixty-page international cooperation agreement written in a foreign legal jargon, ask the tool to map the critical compliance risks, and even generate a script to cross-reference our student database with partner universities. These were tasks that previously required a specialized team or weeks of training; now, it feels like having a highly competent digital assistant that instantly expands my personal boundaries of professional efficacy"*.

This perception of "Cognitive augmentation" as a facilitator of competence is significantly associated with the professional role (A1) ($\chi^2(2) = 28.15$, $p < 0.001$), suggesting that the ability to leverage AI as a force multiplier is unevenly distributed across different levels of the university hierarchy. This uneven distribution reflects hierarchical differences, whereby higher-level roles are more able to leverage AI for complex, autonomy-enhancing tasks, while lower-level administrative staff, who form the majority of the sample, are more exposed to routine uses and verification burdens, limiting the perceived benefits of augmentation. However, this augmentation is counterbalanced by a significant trust gap caused by the probabilistic nature of generative AI. More precisely, due to the system's proclivity for hallucinations, a considerable number of respondents reported a transformative shift in their workflow, transitioning from the role of content authors to that of algorithm auditors.

This shift introduces a significant verification burden. The imperative to meticulously *"verify sources"* and *"validate the* [generated] *content"* suggests that the user must possess a level of expertise that is equal to or exceeds that of the AI tools in order to employ them safely. The statistical findings highlight that this "Role of auditor" acts as a significant barrier and is primarily driven by departmental affiliation (A2) (χ^2 (2) = 11.40, p = 0.003), reflecting how the verification burden varies according to the technical or administrative nature of the tasks. For staff with lower AI literacy, this requirement has the effect of being paralyzing. The apprehension of being misled by a convincing but erroneous output engenders a state of elevated cognitive load, wherein the mental energy expended in supervising the AI surpasses the temporal savings achieved through automated content generation process. This "Literacy and trust gap" is strongly influenced by age group (A4) (χ^2 (1) = 19.20, p < 0.001), validating the observation that younger staff may navigate these risks with greater agility, while older workers perceive the lack of transparency as a direct threat to their professional competence. Consequently, for these users, the tool undermines the need for competence rather than supporting it, leading to an adoption-related state of paralysis.

Furthermore, a deeper, long-term anxiety emerged regarding the phenomenon of cognitive atrophy. Addressing the general perception of AI, several staff members have expressed concerns that the advancement of artificial intelligence may come at the expense of natural intelligence. The fundamental concern is that the practice of outsourcing cognitive effort, even for routine administrative tasks, will ultimately lead to the erosion of the critical thinking skills essential for public service. Participants posed questions regarding the potential development of future generations of workers, speculating whether these individuals might become *"superficial"* or *"intellectually lazy"*, thereby exhibiting an absence of the profound regulatory knowledge that characterises the professional identity of university staff (Tomlinson and Jackson, 2021). Particularly, an experienced administrative collaborator close to retirement captured this generational anxiety with exceptional analytical clarity: *"My real fear is not that the machine is stupid, but that it is too fast and convincing. When you spend thirty years reading laws, internalizing university regulations, and learning how to solve problems through raw mental effort, you build a form of professional competence that is a core part of who you are. If new generations of workers rely entirely on an AI to summarize texts and write responses, they will become superficial and intellectually lazy. They won't possess that profound, organic regulatory knowledge that characterizes our professional identity. If you don't train the cognitive muscle of critical thinking because* [the machine] *does it for you, that muscle will inevitably atrophy, leaving us with a workforce of empty auditors who accept whatever the screen shows them"*.

The Chi-square analysis confirms that the "Risk of cognitive atrophy" is a barrier significantly associated with age group (A4) (χ^2 (1) = 14.45, p = 0.012), indicating that the fear of intellectual erosion is a predominantly generational concern within the administrative workforce. This apprehension acts as a psychological impediment, prompting some employees to deliberately limit their utilisation of the tool, not due to its perceived ineffectiveness, but rather due to their apprehension of its potential efficacy. They regard the engagement with complex tasks as a vital component for preserving their cognitive agility, perceiving the seamless operation of AI as a catalyst for professional obsolescence.

4.4 Relatedness: the human factor as a public sector defence

In conclusion, the dimension of relatedness was identified as the immutable core of the university's identity. In this context, the preservation of human connection was not regarded by participants as a matter of preference, but rather as an imperative that could not be compromised.

The data suggests a pervasive sense of alarm with regard to the sterilization of the workplace. When requested to provide a rationale for their stance, a significant number of respondents articulated a visceral aversion to the notion of AI serving as a *"surrogate for social interaction"*. While the staff appeared favourable to the automation of purely transactional exchanges (e.g. certificate issuance), they established a strict boundary against the introduction of AI tools in student services. In particular, the notion of chatbots replacing student counselling or automated emails substituting for collegial dialogue was not regarded as an innovation, but rather as a deterioration in service quality. An administrative collaborator working at the front-office of a large student counselling centre described this critical boundary with deep emotional and professional resonance: "*Students don't just come to our desks to drop off a form; they often come because they are disoriented, anxious about their future, or experiencing a moment of personal crisis. A chatbot can give them the mathematically correct answer about credits or deadlines, but it cannot offer human comfort or decode a silent cry for help. If we replace our front-offices with automated AI interfaces, we are sterilizing the university* [. . .] *We are transforming a community of learning into a cold, bureaucratic vending machine. Efficiency cannot be bought at the price of complete relational isolation"*.

This qualitative evidence of a collective red line is empirically validated by the Chi-square analysis, which reveals that the "Risk of workplace sterilization" shows no significant correlation with gender (A3) (χ^2 (1) = 0.45, p = 0.502), indicating that the aversion to a cold, automated environment is a sentiment shared equally by all employees.

Indeed, within the culture of the public sector, the provision of physical presence for the user – that is to say, the offering of a listening ear rather than merely a digital output – is a primary source of professional pride and meaning (Anderfuhren-Biget *et al.*, 2010). Consequently, any application of AI that systematically reduces human contact is perceived as a direct thwarting of relatedness. The statistical results further reinforce this idea of an organizational-wide identity: the "Preservation of human connection" ($\chi^2(2)$ = 2.10, p = 0.350) and the defence of a "Relational professional identity" ($\chi^2(2)$ = 3.50, p = 0.174) yielded non-significant results across professional role (A1) and department (A2).

This lack of statistical divergence is highly informative, as it confirms that the human factor is perceived as a non-negotiable pillar of the public mission by the entire workforce, regardless of their specific duties or departmental affiliation. The prevailing sentiment suggests that for these employees, an increase in operational speed that comes at the cost of organisational isolation is considered a failure of the public mission. In other words, a university that prioritises the cold efficiency of an algorithm over the warmth of a community ceases to function as an educational institution, transforming into a mere content delivery platform. A senior academic services coordinator reinforced this shared institutional stance, illustrating how the erosion of relatedness directly threatens public value creation: "*Whether you are a manager or a front-desk operator, we all feel that our professional identity is anchored in public service, which is inherently relational. If an increase in operational speed or a reduction in processing times comes at the cost of organizational isolation, it is a complete failure* [. . .] *A university* simply *ceases to function"*.

The pervasive non-significance of drivers such as age group (A4) in "Countering organizational isolation" (χ^2 (1) = 0.90, p = 0.343) finalizes this narrative, suggesting that the desire for a human-centric workplace is a transversal value that transcends generational divides. This universal defence of relatedness indicates that any AI implementation strategy within higher education TQM frameworks must safeguard the relational ecosystem, as thwarting this need leads to systematic alienation and a loss of public institutional purpose.

4.5 The paradox of AI-driven continuous improvement: a conceptual framework

To integrate and visually synthesize these empirical findings, Figure 1 presents the emergent conceptual framework derived from our empirical analysis. This model does not constitute the deductive theoretical lens established at the outset of the study (i.e. SDT and TQM); rather, it represents an inductive, data-driven mapping of how the conditional logic of AI adoption unfolds within public higher education institutions (HEIs). The model posits that the implementation of AI is not a uniform process but is mediated by a central AI legitimacy threshold. The determination of this threshold is contingent upon a fundamental evaluative question: The question thus arises as to whether AI should be regarded as an assistive infrastructure or a professional substitute.

The framework reveals that the three SDT dimensions do not respond symmetrically to AI integration. When the technology is perceived as assistive infrastructure, it facilitates legitimate adoption by nourishing the agentic side of the self. Within this paradigm, AI functions as a subsidiary instrument that fosters the SDT dimensions of competence – through the automation of routine tasks and enhanced cognitive support – and autonomy – by liberating staff from administrative burdens. This configuration has been demonstrated to engender efficiency gains and to nurture a sustainable cycle of continuous improvement, wherein AI complements human expertise without engendering a threat to professional identity. In this context, autonomy is enhanced as the tool acts as an extension of the professional's will rather than a constraint.

Conversely, when AI integration crosses the legitimacy threshold toward professional substitution, significant professional resistance is triggered. In this scenario, the technology is perceived as an autonomous decision-maker that frustrates the relational and moral self. Here, the core SDT need for relatedness acts as a critical barrier; its frustration leads to a sterilisation of interpersonal service dynamics and the erosion of workplace empathy. Moreover, the framework introduces ethical agency as a professional specification of autonomy. When AI encroaches upon discretionary judgment, it poses a threat to this agency, giving rise to concerns regarding cognitive decline and the perceived abdication of professional responsibility. This process ultimately results in a significant relational loss, indicating that the pursuit of efficiency through substitution has the counterproductive effect of undermining the core public service values of the institution.

The framework underscores that the viability of AI-driven continuous improvement is contingent upon its operation as a "human-in-the-loop" system, thereby ensuring the preservation of boundaries pertaining to professional judgment and the relational intricacies inherent to the public administrative role.

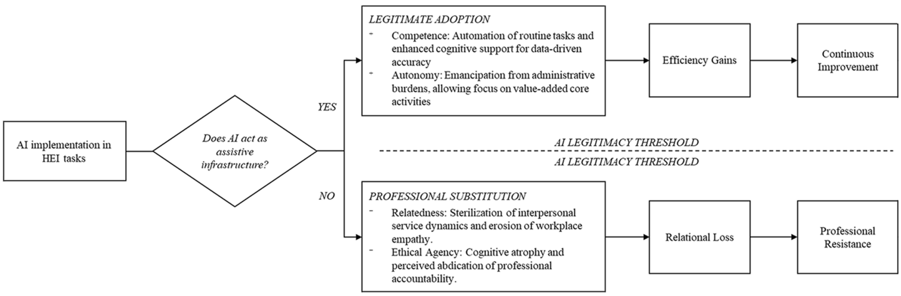

Figure 1. Emergent conceptual framework for AI adoption in HEIs. **Source:** Authors' own work

4.6 Cross-university analysis

To empirically test the stability of the emergent conceptual framework and evaluate how institutional heterogeneity shapes the positioning of the AI legitimacy threshold, a final cross-university bivariate analysis was conducted. The individual coded employee experiences were cross-tabulated against the macro-institutional profiles defined in the methodology: High Digital Maturity HEIs (HDM, $n = 182$) and Low-to-Medium Digital Maturity HEIs (LMD, $n = 148$). This statistical validation determines whether the tension between assistive infrastructure and professional substitution is idiosyncratic or structurally dependent on the university's technological readiness.

As reported in Table 6, significant statistical associations emerged across two of the three primary behavioural dimensions, confirming that institutional context acts as a critical contingency factor for the AI legitimacy threshold. Regarding Competence, the distribution of responses regarding cognitive outcomes varied sharply between the two settings ($\chi^2(1) = 28.45$, $p < 0.001$), with HDM institutions showing a predominant concentration of cognitive augmentation experiences (68.7%) compared to LMD settings (39.2%). This suggests that a robust digital infrastructure acts as a necessary scaffolding that helps employees cross the competence threshold safely.

Similarly, the operationalization of Autonomy revealed a significant institutional divergence ($\chi^2(1) = 10.36$, $p = 0.001$), driven by a higher incidence of job crafting in LMD organizations (54.1%) and a higher perception of behavioural control in HDM structures (63.7%). This counterintuitive finding reveals a hidden cost of high digital maturity: when systems are fully integrated, the automated workflows can tighten administrative compliance, threatening decisional sovereignty.

Conversely, the analysis showed no statistically significant association between institutional maturity and Relatedness dynamics ($\chi^2(1) = 0.76$, $p = 0.383$), with both clusters displaying an overwhelming convergence toward the perception of workplace sterilization (83.0% and 86.5% respectively). This structural invariance underscores that the relational core of the public mission remains an absolute, non-negotiable red line across the entire higher education sector, completely detached from the level of technological sophistication of the individual institution.

Table 6. Chi-square cross-tabulation (institutional maturity vs aggregated SDT dimensions)

SDT construct	Employee experience	AI role	High digital maturity (HDM)	Low-to-medium digital maturity (LMD)	χ^2	df	*p*-value
Autonomy	*Job Crafting/ Emancipation*	Facilitator	66 (36.3%)	80 (54.1%)	10.36	1	0.001**
	Decisional Sovereignty/Control	Barrier	116 (63.7%)	68 (45.9%)			
Competence	*Cognitive Augmentation*	Facilitator	125 (68.7%)	58 (39.2%)	28.45	1	< 0.001***
	Cognitive Atrophy/ Strain	Barrier	57 (31.3%)	90 (60.8%)			
Relatedness	*Relational Preservation*	Facilitator	31 (17.0%)	20 (13.5%)	0.76	1	0.383 (n.s.)
	Workplace Sterilization	Barrier	151 (83.0%)	128 (86.5%)			

Note(s): ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$; n.s. = non-significant

Source(s): Authors' own work

5. Discussion

5.1 Mapping the AI legitimacy threshold in public HEIs

This study set out to explore how AI-enabled continuous improvement is experienced by administrative staff in public Higher Education Institutions, moving beyond purely instrumental perspectives to examine its motivational, relational, and quality-related implications. By adopting a Self-Determination Theory (SDT) lens within a Total Quality Management (TQM) and Quality 5.0 perspective, the findings contribute to a more nuanced understanding of AI adoption in public organizations, where efficiency-driven improvement must be aligned with human-centered value creation. In response to RQa, the results show that AI-driven process improvement generates a fundamentally ambivalent impact on autonomy, competence, and relatedness: while it enhances autonomy and competence when used as an assistive tool that removes repetitive tasks and augments capabilities, it simultaneously frustrates these needs when it threatens decisional sovereignty, increases verification burdens, or creates dependency and cognitive atrophy. Most critically, relatedness emerges as a non-negotiable dimension, as any substitution of human interaction is perceived as a deterioration of service quality rather than an improvement, thereby extending prior research on AI and public value (Van Noordt and Tangi, 2023) by showing that efficiency gains do not automatically translate into quality improvements in relational service contexts. Prior research indicates that combining AI capabilities with human expertise is increasingly necessary across sectors and organizational settings (Parker and Grote, 2022; Ngo, 2025). However, our findings suggest that the form and legitimacy boundaries of this complementarity are context dependent. In public HEIs, where administrative work combines standardized procedures with relational, ethically accountable, and student-facing activities, employees accept AI primarily as a support mechanism for operational efficiency while resisting forms of substitution that threaten discretionary judgment and interpersonal interaction. This indicates that sectoral logics and organizational functions shape not whether AI is accepted, but under what conditions its integration is perceived as legitimate.

In response to RQb, the findings indicate that AI adoption is rarely autonomous but largely driven by controlled forms of motivation associated with technological determinism and fear of obsolescence, thus confirming SDT assumptions (Ryan and Deci, 2024) and extending studies on algorithmic management (Kellogg *et al*., 2020; Jarrahi *et al*., 2023); autonomous motivation emerges only when AI is perceived as assistive infrastructure rather than a professional substitute, preserving human control, interpretability, and opportunities for skill development, which suggests that continuous improvement initiatives risk becoming superficial if not supported by genuine employee internalization.

In response to RQc, the study shows that AI adoption poses a systemic risk to the relational quality of public service, as the reduction of human interaction is interpreted as "workplace sterilization", reinforcing critiques of data-driven universities (Komljenovic *et al*., 2025) and highlighting that, within a TQM perspective, quality in public HEIs must include relational and experiential dimensions rather than being reduced to efficiency metrics.

To visually consolidate these arguments, Table 7 synthesizes the empirical alignment between the quantitative statistical predictors, the core qualitative themes, and their respective theoretical implications within the analysed framework. However, while this baseline framework maps the macro-mechanisms of the AI legitimacy threshold across the aggregated sample, it does not account for how localized organizational environments shape these dynamics – a dimension that requires shifting the analytical focus from individual socio-demographic drivers to macro-institutional configurations.

5.2 Institutional context and the contingent nature of the AI legitimacy threshold

A critical contribution of this study lies in acknowledging that public Higher Education Institutions (HEIs) are not monolithic environments; rather, the dynamic interaction between AI integration and employee psychology is inherently bounded by institutional conditions.

Table 7. Synthesis of findings and theoretical implications

SDT construct	Independent variable and statistical significance	Employee experiences and recurring patterns	Theoretical interpretation
Autonomy	Significant by Professional Role (A1, $p < 0.001$\$) and Department (A2, $p = 0.002$)	Dualism: emancipation from repetitive tasks vs defence of decisional sovereignty	AI is integrated as an assistive infrastructure that supports self-determination only when human discretionary judgment is preserved
Competence	Significant by Professional Role (A1, $p < 0.001$) and Age Group (A4, $p = 0.012$)	Paradox of automation: cognitive augmentation vs role of auditor and risk of cognitive atrophy	Augmentation requires matching individual AI literacy with transparency to avoid high cognitive load, verification overload, and paralysis
Relatedness	Non-significant across Gender (A3), Professional Role (A1), and Age Group (A4)	Universally shared aversion to workplace sterilization and defence of a relational professional identity	The human factor acts as a transversal public sector defence; relational interaction is recognized as an uncompromised dimension of service quality

Source(s): Authors' own elaboration

The quantitative cross-university divergence presented in the findings section (see Section 4.6 and Table 6) is deeply reflected in the nuanced operational realities of the individual sampled HEIs, proving that the proposed "AI legitimacy threshold" does not operate uniformly across all settings, but is closely calibrated by an institution's digital maturity and administrative structure. By moving beyond a universalistic view of AI adoption, these findings validate institutional evolution models (Irani *et al.*, 2023), demonstrating that structural constraints and technological infrastructure act as powerful boundary conditions for quality management.

Regarding the need for Competence, qualitative evidence clarifies the sharp contraction of the threshold observed in low-maturity settings. In Low-to-Medium Digital Maturity HEIs (LMD) – specifically University 4 and 5, which are characterized by a high reliance on legacy paper flows – the paradox of automation manifested with localized intensity; employees expressed deep anxieties regarding accountability, viewing the AI output with suspicion and experiencing data verification as a source of cognitive strain and paralysis. Conversely, in High Digital Maturity institutions (HDM), such as University 1 and 6 (characterized by cloud-based architectures), the AI legitimacy threshold was pushed forward. Administrative staff within these specific settings routinely integrated automated FAQ systems, experiencing an enhancement in their perceived competence as they felt protected by a reliable, integrated infrastructure that minimized verification burdens.

Similarly, the interaction between AI and Autonomy – specifically the dualism between operational emancipation and the defence of decisional sovereignty – was found to be moderated by localized organizational configurations. In universities characterized by decentralized, department-based administrative structures, such as University 3 and 5 (LMD), the perception of AI as a facilitator for job crafting was significantly higher, as employees felt they preserved greater discretionary judgment to integrate AI as a flexible assistive tool tailored to localized problem-solving. Conversely, a distinct structural condition emerged in University 2 (a highly centralized, HDM institution): here, despite the technical readiness, the rigid administrative framework led the majority of respondents to view AI deployment through a compliance-driven lens, exacerbating feelings of technological determinism, micro-management, and threatening their decisional sovereignty.

Intriguingly, while autonomy and competence dimensions fluctuated significantly based on these environmental conditions, the need for Relatedness emerged as an unyielding, cross-institutional constant. Whether in large, highly decentralized campuses like University 3, or in smaller, central-hub institutions like University 4, the rejection of AI applications that substitute human interaction in front-office student support remained absolute and statistically indistinguishable. This cross-sectional consensus signals that while technical competence and operational autonomy are highly contingent on the structural and digital maturity of individual HEIs, the safeguarding of human-centric public values represents a non-negotiable threshold that homogeneously unifies the higher education public sector against the threat of purely efficiency-driven digital transformations.

6. Conclusions and limitations

In conclusion the findings extend the human-AI complementarity literature (Parker and Grote, 2022; Ngo, 2025) by demonstrating that complementarity is not only functional but also motivational and ethical, and by introducing the notion of an AI legitimacy threshold, whereby continuous improvement is enabled only when AI remains embedded within a human-in-the-loop logic that supports, rather than replaces, professional judgment and relational work.

From a theoretical standpoint, this contributes to TQM by conceptualizing AI-enabled continuous improvement as a socio-technical process in which performance depends on the alignment between technological capabilities and the satisfaction of fundamental psychological needs, thus advancing Quality 5.0 perspectives that emphasize human-centricity. From a practical and managerial standpoint, the findings suggest that public HEIs should approach AI adoption not as a standalone technological upgrade but as a structured continuous improvement and work design intervention, requiring the reconfiguration of processes, roles, and responsibilities.

In particular, organizations should explicitly distinguish between back-office automation and decision-making activities, ensuring that AI is deployed to streamline repetitive tasks while preserving human accountability and discretionary judgment in high-stakes decisions. At the same time, managers should embed AI within human-in-the-loop systems, designing workflows that integrate algorithmic support with professional oversight, rather than replacing it. Investments in AI literacy should go beyond technical training and focus on interpretability, critical evaluation, and confidence-building, enabling employees to act as informed supervisors of AI outputs and reducing anxiety, dependency, and verification overload. Furthermore, consistent with TQM principles, organizations should safeguard relational interactions as a core dimension of service quality, avoiding excessive standardization and digital substitution in student-facing activities, and instead leveraging AI to free up time for higher-value relational work. Finally, managers should monitor not only efficiency gains but also employee motivation and perceived service quality as key performance indicators of AI-driven improvement initiatives, as neglecting these dimensions may lead to defensive adoption, erosion of professional identity, and ultimately to a misalignment between process optimization and public value creation.

Despite these contributions, the study is subject to several limitations, including its focus on a single national context and administrative staff, the cross-sectional nature of the data, and the reliance on self-reported perceptions, which may limit generalizability and the ability to capture longitudinal dynamics. In particular, the Italian institutional and cultural context may influence employees' perceptions and acceptance of digital and AI-enabled work practices, as prior research suggests that the adoption and interpretation of AI tools may vary according to organizational and cultural characteristics (e.g. Pfranger and Mayrhofer, 2026).

A further demographic limitation pertains to the age distribution of the sample, which is predominantly characterised by employees in mid-to-late career stages (with over 60% of participants aged 50 or above). While this imbalance does not stem from a sampling bias, it accurately reflects the historical structural ageing that has characterised the Italian public administration and public higher education sector. However, as extensively documented in the extant literature on technology adoption, age and generational cohorts can significantly influence attitudes towards digital innovation, psychological adaptation, and professional identity. It is important to note that younger employees, or those classified as digital natives, may manifest distinct behavioural patterns, elevated levels of digital readiness, or alternative mechanisms of adaptation when confronted with the integration of AI. Consequently, while the present sample accurately reflects the current demographic reality of the analysed higher education institutions (HEIs), it has accentuated specific concerns regarding the loss of decisional sovereignty and cognitive atrophy.

In addition to these sample-specific boundaries, another limitation of the study, which is common to all analyses of AI's impact, lies in the fact that AI-related technology is evolving rapidly, and so are the performance levels of AI systems. As a result, it is difficult to provide organizational and managerial recommendations based on the current state of AI development, since in the near future these capabilities may change radically.

Future research could address these limitations by adopting longitudinal and comparative designs, extending the analysis to multiple stakeholders, and empirically testing the proposed framework, particularly the role of the AI legitimacy threshold in shaping sustainable, human-centered continuous improvement processes. Cross-country comparisons may be particularly valuable in assessing how institutional and cultural contexts shape the legitimacy and acceptance of AI-enabled continuous improvement in public organizations.

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