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From Innovation to Exhaustion? A Structural Analysis of Intelligent Automation's Effects on Burnout, Technology Acceptance, and Work Engagement in Airport Organizations

Abstract. *Intelligent automation is increasingly reshaping the working environment in airports, yet its implications for staff remain underexplored. This study examines how employees perceive and respond to automated systems by linking technology acceptance to the digital job conditions created by automation and their psychological outcomes. Anchored in the Technology Acceptance Model (TAM) and the Job Demands–Resources (JD-R) framework, we conceptualise digital job demands and digital job resources as higher-order constructs to capture the complexity of technology-mediated work. Data were collected from 126 Romanian airport employees who routinely interact with biometric gates, automated baggage handling, and AI-driven maintenance systems. Using Partial Least Squares Structural Equation Modelling (PLS-SEM), nine hypotheses were tested. The analysis shows that perceived ease of use and the availability of digital job resources foster technology acceptance, which in turn mediates their positive effect on work engagement. By contrast, perceived usefulness and digital job demands show no direct influence, whereas burnout amplifies the detrimental impact of job demands on engagement. These results highlight the importance of complementing digital transformation in airports with supportive practices.*

Keywords: *intelligent automation, employee engagement, burnout, airports, structural equation modelling,*

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1. Introduction

The rapid expansion of intelligent automation is transforming how organisations design and manage work, particularly in technology-intensive service industries. Airports are among the most active adopters of these systems, which are transforming the operational environment of tourism and transportation. To enhance productivity and improve the passenger experience, biometric check-in, AI-powered predictive maintenance, automated baggage handling, and digital navigation tools are widely adopted (Agrawal et al., 2024). These technologies offer more sustainable and scalable services, while reducing human error and increasing efficiency, but they also raise concerns regarding their impact on frontline employees (Borysiuk & Bugayko, 2025).

Research to date has largely concentrated on efficiency gains and technological performance, paying far less attention to employees' psychological states and job-related outcomes. Automation can act both as a job demand – by increasing mental load and system dependency – and as a job resource – by enhancing collaboration and autonomy (Liu et al., 2014). This dual pathway reflects the Job Demands–Resources (JD-R) framework (Bakker & Demerouti, 2017). At the same time, the Technology Acceptance Model (TAM) provides a useful lens for understanding how employees perceive and adopt digital tools (Davis, 1989). When digital demands outweigh resources, strain and disengagement may emerge, with burnout further shaping these relationships, particularly in high-stress, continuous-operation environments such as airports (Milbredt et al., 2022).

Despite these advances, research remains fragmented, with limited evidence on how technology acceptance, digital job demands, digital job resources, and employee well-being interact within highly automated airport environments. Existing studies have typically addressed these dimensions separately rather than within an integrated framework (e.g., Tarafdar et al., 2015; Molino et al., 2020b). In particular, the combined role of engagement and burnout in shaping employees' responses to intelligent automation remains insufficiently explored, especially in continuous-operation contexts such as airports.

This study investigates the interaction between intelligent automation, technology acceptance, and employee psychological outcomes in airports by integrating the JD-R and TAM frameworks. Using survey data from 126 employees who interact with facial recognition, automated check-in, and AI-based maintenance systems, Partial Least Squares Structural Equation Modelling (PLS-SEM) is applied to test three research questions: (1) how perceptions of ease of use and usefulness shape technology acceptance; (2) how digital job demands and resources influence engagement through technology acceptance; and (3) how burnout moderates the relationship between job demands and engagement.

By doing so, the study makes two main contributions. First, it extends existing research by integrating technology acceptance and job demands-resources perspectives within a single framework applied to intelligent automation contexts. Second, it provides empirical evidence on how engagement and burnout jointly shape employees' responses to automation in airport environments, offering relevant implications for both theory and managerial practice.

2. Literature review

2.1 TAM and JD-R Integration

The Technology Acceptance Model (TAM) developed by Davis (1989), is one of the most important theoretical frameworks for understanding the acceptance of new technologies. At its core, the model highlights two constructs – perceived usefulness (PU) and perceived ease of use (PEOU) – which shape user attitudes and behavioural intentions. Together, these dimensions are considered strong predictors of both initial acceptance and long-term use. While TAM has been widely applied and adapted across many disciplines, its standard formulation pays relatively little attention to the broader organisational or psychosocial factors that also influence how technologies are adopted in everyday practice.

In response to this limitation, scholars have increasingly turned to combining TAM with the Job Demands–Resources (JD-R) framework (Bakker & Demerouti, 2017). The JD-R model illustrates how work demands - such as digital dependency or task intensification - can steadily drain energy and erode well-being, while resources such as autonomy, supportive systems, or collaboration tend to stimulate motivation and foster engagement. What makes this joint perspective valuable is that it allows the researcher to capture, within a single framework, both the cognitive side of technology adoption, as theorised by TAM, and the contextual or emotional dimensions of work, which fall within the scope of JD-R - two aspects that are often examined in isolation but rarely in tandem.

In highly automated settings such as airports, where technologies ranging from facial recognition and self-check-in kiosks to AI-based maintenance are steadily reshaping conventional job tasks, an integrated framework of this kind proves particularly useful. It not only allows researchers to explore how the work environment influences employees' motivation and willingness to engage with digital systems, but also how they evaluate such systems in terms of usefulness and ease of use – a dual perspective that is often overlooked. The importance of integrating these two frameworks has been highlighted in empirical studies. For example, Shamsi et al. (2021) reported that, in the context of remote work during the COVID-19 pandemic – when levels of employee engagement were under scrutiny - the combined use of TAM and JD-R delivered stronger explanatory power than either model used independently.

2.2 Perceived Ease of Use, Perceived Usefulness and Technology Acceptance

Perceived Ease of Use (PEOU) is a key construct in TAM, defined as the belief that interacting with a system requires little effort (Davis, 1989). In technology-based services such as tourism and airport operations, PEOU consistently predicts acceptance, as employees and passengers tend to prefer tools that are intuitive and easy to use. Auer et al. (2024) provide evidence that passengers' willingness to interact with AI-based chatbots at airports is strongly influenced by their perception of ease of use, reinforcing the argument that system simplicity is not a secondary feature, but a decisive factor in shaping user attitudes. Hence, we propose:

H1: Perceived Ease of Use (PEOU) significantly influences Technology Acceptance (ACT) in airport automation.

Perceived Usefulness (PU), the second core construct of TAM, refers to the extent to which technology enhances performance (Davis, 1989). A meta-analysis by Li et al. (2024), covering over 13,000 participants in tourism and hospitality, identifies PU as the strongest predictor of adoption for mobile and AI-based services. This suggests that even in automated contexts, users balance perceived usefulness with ease of use when forming acceptance judgments. Hence, we propose:

H2: Perceived Usefulness (PU) positively influences Technology Acceptance (ACT).

2.3 Digital Job Demands and Resources in Technology Acceptance

The JD-R framework argues that all occupations can be described in terms of demands and resources that, through their interaction, shape not only employee well-being, but also motivation and performance outcomes (Demerouti et al., 2001). As intelligent automation proliferates, employees are confronted with new categories of stressors, including the constant flow of notifications and an increased reliance on algorithmic systems that mediate key aspects of their work. In this study, these pressures are conceptualised as Digital Job Demands (DJD), a second-order construct integrating availability, work intensification, and dependency on intelligent automation. Such demands can fragment attention, disrupt established workflows, and erode performance over time (Bon & Shire, 2019), while also amplifying techno-strain, a recognised barrier to technology adoption (Marsh et al., 2024). On this basis, we propose the following.

H3: DJD negatively influences Technology Acceptance (ACT).

In contrast, the JD-R model also underscores the protective and motivational role of job resources. In digitalised workplaces, Digital Job Resources (DJR) can be understood as a higher-order configuration of collaboration opportunities, perceived efficiency, and autonomy. These resources not only buffer the negative impact of Digital Job Demands (DJD), but also enhance employees' ability to adapt to and effectively use new technological systems (Bakker & Demerouti, 2007). Prior studies suggest that when workplaces are rich in supportive resources, performance expectancy is strengthened and aligns with the central assumptions of TAM, thereby fostering user acceptance and sustained engagement with digital tools (Miskolczi et al., 2021; Walczuch et al., 2007). On this basis, we propose the following.

H4: Job Resources (DJR) positively influence Technology Acceptance (ACT).

2.4 Digital Job Demands, Resources, and Work Engagement

One of the main motivational outcomes in the JD-R framework is work engagement, defined as a positive and fulfilling state of vigour related to one's work (Schaufeli et al., 2002). The emergence of intelligent automation introduces additional pressures that may undermine this state, particularly in services industries that rely heavily on technology, such as travel and tourism.

According to Tarafdar et al. (2015), the health-impairment process within the JD-R framework suggests that Digital Job Demands (DJD) can deplete employees' energy, reduce their sense of control over their work, and ultimately lower their levels of engagement. Building on this reasoning, we propose:

H5: Digital Job Demands (DJD) negatively influence Work Engagement (ENG).

Conversely, Digital Job Resources (DJR) are understood to function both as protective mechanisms and as motivational drivers, as they enhance intrinsic motivation and increase employees' willingness to invest effort, particularly when such resources are perceived as supportive rather than restrictive or controlling (Bakker & Demerouti, 2007; Zoonen et al., 2021). On this basis, we propose the following.

H6: Digital Job Resources (DJR) positively influence Work Engagement (ENG).

2.5 Technology Acceptance and Work Engagement

Work engagement, defined as a positive, fulfilling work-related state of vigour, is a key motivational outcome for employees in technology-intensive workplaces (Schaufeli et al., 2002). In settings marked by rapid digital transformation, sustaining engagement becomes critical for ensuring both service quality and employee well-being. Within this framework, Technology Acceptance (ACT) emerges as a central factor, as it directly shapes employees' attitudes toward intelligent automation and, in turn, influences both the ease with which such systems become integrated into everyday workflows and the extent to which employees feel motivated to use them (Venkatesh & Davis, 2000). Technologies can further enhance intrinsic motivation when they are perceived as satisfying fundamental psychological needs, in ways that are difficult to replicate through external incentives alone (Deci & Ryan, 2000). Based on this reasoning, we propose:

H7: Technology Acceptance (ACT) positively influences Work Engagement (ENG).

2.6 Technology Acceptance as a Mediator Between Digital Job Resources and Work Engagement

Digital Job Resources (DJR), including forms of collaboration enabled by automation, perceived efficiency, and a sense of autonomy, are generally understood as critical supports that help employees to cope with the pressures introduced by intelligent automation. In work environments where technology plays a dominant role, these resources are theorised not only to facilitate the acceptance of digital systems, but also to strengthen motivational outcomes, particularly work engagement, by reducing demands while simultaneously fostering opportunities for growth and development (Bakker & Demerouti, 2007).

Previous research suggests that Technology Acceptance (ACT) mediates the relationship between job resources and engagement outcomes, highlighting its role as a psychological mechanism through which digital supports translate into increased motivation (Molino et al., 2020a). Building on these considerations, we propose the following:

H8: Technology Acceptance (ACT) mediates the relationship between Digital Job Resources (DJR) and Work Engagement (ENG).

2.7 Burnout as a Moderator Between Digital Job Demands and Work Engagement

Burnout, defined as a prolonged response to chronic work stress characterised by exhaustion, cynicism and reduced effectiveness (Schaufeli & Enzmann, 1998), represents a central outcome of excessive job demands in the JD-R model, particularly when resources are insufficient (Bakker & Demerouti, 2007). Empirical evidence suggests that burnout alters the way job demands affect employees; it has been associated with declines in both safety and engagement across multiple sectors (Nahrgang et al., 2011), and has also been shown to mediate or moderate demand-ability relationships in more recent studies (Debets et al., 2022). In highly automated workplaces such as airports, elevated Digital Job Demands (DJD) can exhaust employee resources and increase burnout, which in turn weakens engagement even when supportive conditions are present (Crawford et al., 2010). Building on this reasoning, we propose:

H9: Burnout (BRN) moderates the relationship between Digital Job Demands (DJD) and Work Engagement (ENG), such that higher levels of burnout amplify the negative effect of job demands on engagement.

Drawing together the theoretical arguments outlined above, the research framework proposed in this study (Figure 1) integrates constructs from both TAM and JD-R in order to empirically examine the hypothesised relationships.

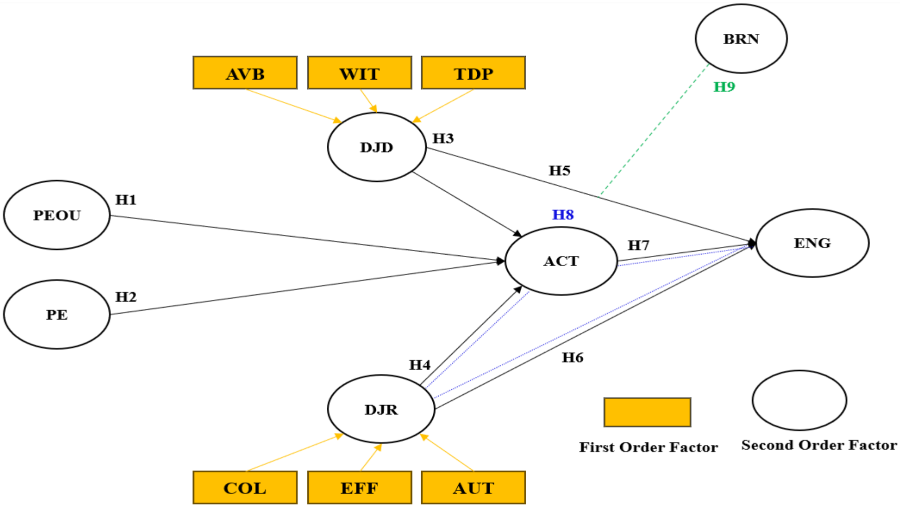

Figure 1. Research Framework

Orange lines are formative indicators and bold lines are hypotheses. Blue dotted lines denote mediated role (H8). Green dashed lines denote moderated role (H9).

Source: Developed by authors.

3. Methodology

Based on the Job Demands–Resources (JD-R) model and the Technology Acceptance model (TAM), this quantitative, cross-sectional study investigates the effects of intelligent automation on employee engagement, acceptance, and well-being in Romanian airports.

Data were collected through an online questionnaire administered between November 2024 and January 2025 to frontline and administrative staff who regularly interact with biometric gates, automated baggage handling, AI-based maintenance and digital wayfinding; participation was voluntary and anonymous, yielding 126 valid responses. The questionnaire used a seven-point Likert scale ranging from 1 (“strongly disagree”) to 7 (“strongly agree”). The items were adapted from scientifically validated scales and pilot tested for contextual fit. Perceived Ease of Use (PEOU) referred to how easy employees considered intelligent automation systems to understand and use. *PEOU* was measured with 4 items, such as “Interacting with intelligent automation systems is clear and easy to understand,” (Pizzi et al., 2020). *Perceived Usefulness (PU)* captured the extent to which these systems were seen as improving job performance, and included 3 items such as “Using intelligent automation systems improves my job performance” (Pizzi et al., 2020). Engagement (ENG) reflected employees’ energy and involvement at work, and was assessed with 3 items such as “I feel full of energy at work” (Korunka et al., 2009). Technology Acceptance (ACT) reflected employees’ overall acceptance of using intelligent automation systems at work and was measured with 3 items such as “I am satisfied with the performance of intelligent automation systems” (Popescu et al., 2025).

Digital Job Demands (DJD) were captured through availability, work intensification, and dependency, and were measured with 3 items including "I often feel overwhelmed because intelligent automation systems have allowed too many people to have access to my time", "Intelligent automation systems force me to do more work than I can handle" and "Slowdowns or downtime in intelligent automation systems directly impact my performance" (Molino et al., 2020b).

Digital Job Resources (DJR) were conceptualised through three dimensions: collaboration, perceived efficiency and autonomy – and were measured with 3 items including "In my organisation, the sharing of work-related information through intelligent automation systems is excellent", "Overall, I believe that intelligent automation systems have improved my productivity at work," and "Automation systems help me decide independently how to perform my tasks" (Malinowska et al., 2018). Burnout (BRN), included as a moderating variable, was measured with 4 items such as "I frequently feel physically exhausted at work" (Vuori et al., 2019).

The demographic profile of the respondents is presented in Table 1. The sample included 126 airport employees, predominantly aged between 25–34 years, with a relatively balanced gender distribution. Most of the respondents had completed high school or undergraduate studies. In terms of professional experience and familiarity with intelligent automation systems, participants exhibited diverse levels across both dimensions.

Table 1. Sample demographics (n = 126)

Variable	n	%	Variable	n	%
Age			**Gender**		
Under 25 years	39	30.95	Male	57	45.24
25–34 years	43	34.13	Female	65	51.59
35–44 years	35	27.78	Prefer not to answer	4	3.17
45–54 years	8	6.35	**Highest level of education completed**		
55 years and over	1	0.79	High school	55	43.65
Professional experience			Bachelor's degree	46	36.51
Less than 3 years	48	38.10	Master's degree	25	19.84
3–5 years	26	20.63	**Experience with intelligent automation at work**		
6–10 years	18	14.29	Beginner	23	18.25
11–15 years	13	10.32	Intermediate	51	40.48
16–20 years	13	10.32	Advanced	43	34.13
21–25 years	6	4.76	Expert	9	7.14
26–30 years	0	0.00			
31–35 years	1	0.79			
36–40 years	1	0.79			

Note: Percentages may not total exactly 100 due to rounding.

Source: Developed by authors.

Because the model integrates multiple latent constructs - including two higher-order variables and a moderator – Partial Least Squares Structural Equation Modelling (PLS-SEM) was applied using SmartPLS 4, which is appropriate for complex models and relatively small to medium samples (Hair et al., 2024). The sample of 126 valid responses exceeds the ‘10-times rule’ and minimum power requirements for PLS-SEM, enabling reliable estimation of path coefficients, as well as mediation and moderation effects (Hair et al., 2024). To further support this, an a priori power analysis conducted using G*Power indicated that a minimum of 108 respondents was required to detect a medium effect size ($f^2 = 0.15$) at $\alpha = 0.05$ and a statistical power of 0.90 in a model with four predictors. Therefore, the sample size can be considered adequate to test the proposed relationships, particularly given the study’s focus on a specialised group of airport employees interacting with intelligent automation systems.

4. Results and discussion

4.1 Measurement model

To evaluate the reliability and convergent validity of the measurement model, Cronbach’s Alpha (α), Composite Reliability (CR), and Average Variance Extracted (AVE) were assessed for each latent construct (see Table 2), while the threshold values considered acceptable were $\alpha \geq 0.70$, $CR \geq 0.70$, and $AVE \geq 0.50$, as recommended by Hair et al. (2020).

All constructs displayed high internal consistency, with Cronbach's Alpha values ranging from 0.869 (ENG) to 0.982 (EFF), indicating that the items reliably measure their respective constructs. The robust reliability of each construct is demonstrated by Composite Reliability (CR) values greater than 0.90. Convergent validity was also supported by the AVE values for all constructs, which ranged from 0.793 (ENG) to 0.982 (EFF), significantly above the 0.50 minimum threshold (Hair et al., 2020). Strong standardised factor loadings were also displayed by each item, all of which were above the 0.70 cutoff, suggesting that each observed variable accurately reflects its underlying latent construct. Overall, the results of Table 2 confirm that the reflective measurement model demonstrates satisfactory levels of internal consistency, reliability, and convergent validity. Although some AVE values are relatively high, this should not be interpreted in isolation, as AVE should be considered together with other measurement criteria (Hair et al., 2020; Sarstedt et al., 2019). To further assess construct distinctiveness, discriminant validity was evaluated using the HTMT criterion (see Table 3), which confirms that the constructs are empirically distinct. These results further suggest that no conceptual overlap exists among the constructs, supporting their distinctiveness. Therefore, the high AVE values do not indicate problematic redundancy.

Table 2. Factor loadings, reliability, and validity (n=126)

Variables / Items	Factor loading	Cronbach's α	CR	AVE
ACT		0.967	0.978	0.938
ACT1	0.967			
ACT2	0.974			
ACT3	0.964			
AUT		0.972	0.982	0.948
AUT1	0.977			
AUT2	0.972			
AUT3	0.971			
AVB		0.893	0.927	0.762
AVB1	0.735			
AVB2	0.920			
AVB3	0.929			
AVB4	0.895			
BRN		0.911	0.937	0.789
BRN1	0.931			
BRN2	0.896			
BRN3	0.947			
BRN4	0.766			
COL		0.970	0.978	0.918
COL1	0.940			
COL2	0.971			
COL3	0.960			
COL4	0.960			
EFF		0.982	0.991	0.982
EFF1	0.991			
EFF2	0.991			
ENG		0.869	0.920	0.793
ENG1	0.881			
ENG2	0.913			
ENG3	0.876			
PEOU		0.942	0.958	0.852
PEOU1	0.944			
PEOU2	0.887			
PEOU3	0.956			
PEOU4	0.904			
PU		0.962	0.976	0.930

Variables / Items	Factor loading	Cronbach's α	CR	AVE
PU1	0.966			
PU2	0.969			
PU3	0.958			
TDP		0.946	0.961	0.861
TDP1	0.907			
TDP2	0.948			
TDP3	0.943			
TDP4	0.913			
WIT		0.955	0.967	0.881
WIT1	0.929			
WIT2	0.940			
WIT3	0.939			
WIT4	0.945			

Note: All items were measured on a seven-point Likert scale ranging from 1 ("strongly disagree") to 7 ("strongly agree"). PEOU = Perceived Ease of Use; PU = Perceived Usefulness; ACT = Technology Acceptance; ENG = Work Engagement; BRN = Burnout; AVB = Availability; WIT = Work Intensification; TDP = Technology Dependency; COL = Collaboration; EFF = Efficiency; AUT = Autonomy.

Source: Developed by the authors based on calculations from SmartPLS.

In structural equation modeling, the Heterotrait–Monotrait (HTMT) ratio is a widely applied criterion for evaluating discriminant validity. Its purpose is to determine whether constructs that are theoretically distinct are also empirically distinguishable. As noted by Benitez et al. (2020), an HTMT value of 0.90 is commonly used as a reference point. The HTMT results (see Table 3) indicate that the constructs are sufficiently distinct, supporting the establishment of discriminant validity. This finding suggests that the constructs capture conceptually different phenomena, as intended.

Table 3. Discriminant validity using HTMT

	ACT	AUT	AVB	BRN	COL	EFF	ENG	PEOU	PU	TDP	WIT
ACT											
AUT	0.692										
AVB	0.138	0.210									
BRN	0.105	0.055	0.322								
COL	0.629	0.773	0.352	0.036							
EFF	0.759	0.881	0.162	0.043	0.776						
ENG	0.494	0.307	0.213	0.482	0.417	0.306					
PEOU	0.738	0.589	0.173	0.144	0.461	0.636	0.497				

	ACT	AUT	AVB	BRN	COL	EFF	ENG	PEOU	PU	TDP	WIT
PU	0.753	0.588	0.077	0.064	0.489	0.648	0.362	0.747			
TDP	0.246	0.233	0.360	0.330	0.273	0.306	0.186	0.210	0.197		
WIT	0.163	0.156	0.651	0.405	0.051	0.129	0.052	0.142	0.241	0.408	

Source: Developed by the authors based on calculations from SmartPLS.

In this study, DJD and DJR are conceptualised as second-order factors (SOF), each constructed formatively through their respective first-order factors (FOF). DJD includes availability (AVB), work intensification (WIT), and technology dependency (TDP), while DJR includes collaboration (COL), efficiency (EFF), and autonomy (AUT). Because the formative specification integrates different but complementary components, the model is able to capture the multidimensional nature of these higher-order constructs. In accordance with the recommendations of Hair et al. (2020) and Sarstedt et al. (2019), specific indicators were used to evaluate the validity of the second-order constructs, including outer weights, t-statistics, p-values, outer loadings, and VIF (Variance Inflation Factor) (see Table 4). The analysis showed that all outer weights associated to the first-order factors within both DJD and DJR reached statistical significance, with resulting p values < 0.05.

Table 4. Second Order Factor (SOF) Validity

SOF	FOF	Outer Weight	T Statistics	P Values	Outer Loadings	VIF
DJD	AVB	0.596	1.934	0.027	0.706	1.61
	WIT	0.602	1.968	0.026	0.887	1.692
	TDP	0.855	1.842	0.033	0.877	1.198
DJR	COL	0.345	18.702	0.000	0.898	2.575
	EFF	0.381	20.072	0.000	0.945	4.347
	AUT	0.351	20.222	0.000	0.939	4.252

Note. DJD = Digital Job Demands; DJR = Digital Job Resources; SOF = Second Order Factor, FOF = First Order Factor, T = t – statistics, P = Probability (P) value, VIF = Variance Inflation Factor.

Source: Developed by the authors based on calculations from SmartPLS.

This outcome suggests that each dimension makes a meaningful and distinct contribution to its corresponding higher-order construct. Outer loadings for all FOF exceeded the threshold of 0.50, ranging from 0.706 to 0.945, confirming the relevance and strength of the relationships between the SOF and their formative indicators (Sarstedt et al., 2019). The results show that each FOF accurately reflects the corresponding SOF, with a range of 1.198 to 4.347, all remaining below the conservative threshold of 5, indicating that multicollinearity is not a concern in this model (Sarstedt et al., 2019).

4.2 Structural model

Since the data did not satisfy the multivariate normality assumption, the Partial Least Squares (PLS) bootstrapping procedure with 5000 subsamples was employed to test the proposed relationships (Hair et al., 2020). The analysis provides estimates for the path coefficients (β), standard errors, t-values, and p-values, which indicate the strength and significance of the hypothesised paths (see Table 5). The model explains 62.1% of the variance in ACT ($R^2 = 0.621$) and 54.2% of the variance in ENG ($R^2 = 0.542$), demonstrating a substantial level of explanatory power.

Table 5. Hypotheses testing

Hypotheses		β	SD	T	P-value	Result
H1:	PEOU→ACT	0.344	0.107	3.202	0.001	Confirmed
H2:	PU→ACT	-0.110	0.119	0.927	0.177	Unconfirmed
H3:	DJD→ACT	0.044	0.083	0.529	0.298	Unconfirmed
H4:	DJR→ACT	0.623	0.173	3.602	0.000	Confirmed
H5:	DJD→ENG	-0.328	0.148	2.217	0.013	Confirmed
H6:	DJR→ENG	0.001	0.113	0.011	0.496	Unconfirmed
H7:	ACT→ENG	0.258	0.126	2.039	0.021	Confirmed

Note: PEOU = Perceived Ease of Use; PU = Perceived Usefulness; ACT = Technology Acceptance; DJD = Digital Job Demands; DJR = Digital Job Resources; ENG = Work Engagement; B = Beta Coefficient, SD = Standard Deviation, T = t – statistics, P = Probability (P) value; *Relationships are significant at P-value < 0.05.

Source: Developed by the authors based on calculations from SmartPLS.

The findings support H1, showing that perceived ease of use (PEOU) significantly increases Technology Acceptance (ACT) (β = 0.344, t = 3.202, p = 0.001). H2 is rejected, as Perceived Usefulness (PU) has no significant effect on ACT (β = -0.110, t = 0.927, p = 0.177). Digital Job Demands (DJD) also do not significantly influence ACT (β = 0.044, t = 0.529, p = 0.298), and therefore H3 is not supported. However, Digital Job Resources (DJR) have a strong and significant impact on ACT (β = 0.623, t = 3.602, p < 0.001), supporting H4. In relation to engagement, DJD has a significant negative effect on ENG (β = -0.328, t = 2.217, p = 0.013), supporting H5, whereas DJR does not significantly influence ENG (β = 0.001, t = 0.011, p = 0.496), and thus H6 is not supported. Finally, ACT has a significant positive effect on ENG (β = 0.258, t = 2.039, p = 0.021), supporting H7.

4.3 Mediation analysis

Hypothesis 8 investigates whether the relationship between DJR and ENG operates through ACT as a mediating construct. The results showed that DJR exerted a positive, though marginally non-significant, influence on ENG (β = 0.162, t = 1.692; see Table 6).

Table 6. Mediation analysis

	Total Effects		Direct Effects		Indirect Effects				Results
H6:	β	T	β	T	H8:	β	T	P	
DJR-ENG	0.162	1.692	0.001	0.011	DJR-ACT-ENG	0.161	1.999	0.023	Confirmed

Note: H=Hypothesis, B = Beta Coefficient, T = t – statistics, P = Probability (P) value; *Relationships are significant at P-value < 0.05.

Source: Developed by the authors based on calculations from SmartPLS.

Once ACT was introduced into the model, however, the direct path between DJR and ENG became non-significant (β = 0.001, t = 0.011), whereas the indirect path via ACT yielded a positive and statistically significant effect (β = 0.161, t = 1.999, p = 0.023). Taken together, these findings indicate a case of full mediation, meaning that ACT entirely transmits the effect of DJR on ENG, thus supporting Hypothesis 8.

4.4 Moderation analysis

H9 proposes that Burnout (BRN) moderates the relationship between DJD and Engagement (ENG), such that the level of burnout influences this relationship. This study assessed the moderating impact of burnout on the association between DJD and ENG. Without the interaction term (BRN x DJD), the R^2 for ENG was 0.223, while it increased to 0.542 after the interaction effect was included, indicating a substantial improvement in the model's explanatory power and accounting for 54.2% of the variance in ENG.

The significance of the moderation effect was further examined, and the results show that the interaction between BRN and DJD has a negative and significant impact on ENG (β = -0.471, t = 2.123, p = 0.034), thus supporting H9. The calculated f^2 effect size for the moderation was 0.222. This value falls between medium and large according to Cohen's (1988) (0.02 = small, 0.15 = medium, 0.35 = large). These findings suggest that burnout significantly influences how DJD affects engagement and contributes meaningfully to explaining the variance in ENG.

4.5 Discussion

This study set out to explore how intelligent automation, technology acceptance, and employee engagement intersect within airport operations, using an integrated framework that combines the Technology Acceptance Model (TAM) and the Job Demands–Resources (JD-R) model. By incorporating burnout as a moderator, it provides a layered account of how digital systems shape employee behaviour, simultaneously addressing cognitive processes (acceptance), contextual dynamics (demands and resources), and emotional factors (burnout). In doing so, the study moves beyond the single-lens perspective that has dominated much of the research on automation and tourism.

The results reinforce one of the central premises of TAM, namely that Perceived Ease of Use (PEOU) consistently emerges as a strong predictor of Technology Acceptance (ACT), underscoring the importance of intuitive design in shaping user attitudes (Venkatesh & Davis, 2000). However, contrary to expectations derived from TAM, no significant relationship was found between Perceived Usefulness (PU) and ACT. In highly regulated settings, where technology use is largely mandatory, ease of use appears to outweigh functional value; in other words, perceived usefulness alone may not drive acceptance unless it is accompanied by low cognitive effort and a clear sense of personal relevance (Weiner, 2009).

A more nuanced picture emerges for Digital Job Demands (DJD) and Digital Job Resources (DJR). DJD - such as constant availability, workload intensification, and dependency on automation - did not directly influence ACT, but were associated with lower engagement at higher levels of burnout, reflecting the JD-R health impairment process (Russell et al., 2020). In contrast, DJR (system support, autonomy, and digital feedback) significantly predicted ACT, but did not have a direct effect on engagement. Instead, ACT mediated the relationship between DJR and ENG, suggesting that supportive conditions translate into motivation only when employees internalise and accept the technology.

Furthermore, the findings indicate that even in the presence of abundant resources, engagement does not automatically follow unless employees perceive the system as intuitive, controllable, and personally meaningful. Burnout emerged as a salient moderator with prior evidence on techno-strain in digital environments (Tarafdar et al., 2015). Rather than functioning solely as a downstream outcome of job demands, burnout acts as a lens through which such demands deplete energy and weaken motivation. In technology-intensive work environments, the sustainability of digital transformation depends on maintaining a balance between demands, resources, and employee well-being.

Taken together, the findings strengthen the TAM–JD-R framework by demonstrating how cognitive, contextual, and emotional factors jointly shape the employee experience in complex, technology-driven environments such as airports and smart tourism systems.

5. Conclusions

This research refines the Technology Acceptance Model by demonstrating that Perceived Ease of Use can outweigh Perceived Usefulness in environments where the adoption of automation is mandatory. It also extends the Job Demands–Resources model by conceptualising Digital Job Demands and Digital Job Resources as second-order constructs and by treating burnout as an active moderator rather than a static outcome. The study further shows that Technology Acceptance serves as a mediator between Digital Job Resources and work engagement, offering an explanation for why supportive digital environments often promote acceptance but fail to translate into stronger engagement unless employees interpret and internalise the technology in a positive way.

For both managers and policymakers, the results translate into concrete lessons for practice. Usability and genuine employee participation should be regarded as essential rather than optional; systems need to be intuitive, co-designed with frontline staff, and supported by clear communication of benefits alongside realistic expectations of their impact. Equally important, digital job resources such as training opportunities, autonomy-supporting tools, and responsive support channels should be systematically integrated into rollout strategies so as to reinforce technology self-efficacy (Zoonen et al., 2021). Managers, meanwhile, must remain attentive to the pressures created by digital job demands; mechanisms such as smart workload tracking, fair and transparent shift scheduling, and policies such as the "right to disconnect" can alleviate techno-stress and its negative outcomes (Tarafdar et al., 2015). Since burnout amplifies the harmful effects of such demands, provisions for mental-health support, structured recovery breaks, and flexible work arrangements should be treated not as optional perks but as part of the organisation's core infrastructure (Sonnentag, 2018). In other words, automation will only deliver promised gains if organisations invest as much in the human side of change as they do in the technical side.

Several limitations should be considered when interpreting these results. First, although the sample of 126 respondents was adequate for the statistical approach employed, it remains relatively modest for drawing broader generalisations. Second, the study was conducted in a specific context – Romanian airports – which may limit the transferability of the findings to other sectors or countries. Therefore, the results should be interpreted as reflecting a particular automation-intensive environment rather than being universally generalisable. Finally, the cross-sectional design captures employees' perceptions at a single point in time and does not allow for strong causal inferences.

Future research could build on these findings by testing the model on larger and more diverse samples, both across countries and in other sectors where automation plays an important role. It would also be valuable to explore how digital job demands and resources are experienced in everyday work using qualitative or mixed-method approaches, such as interviews or diary studies. Such designs could capture day-to-day variations in techno-strain more effectively than cross-sectional surveys.

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