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Generation Z Employees' Acceptance and AI Use Intensity: A Moderated Mediation Model of Psychological Safety, Technostress, and Trust

Claudia-Elena Țuclea * and Luciana-Floriana Poenaru

Department of Tourism and Geography, Bucharest University of Economic Studies, 010404 Bucharest, Romania; luciana.holostencu@com.ase.ro
* Correspondence: claudia.tuclea@com.ase.ro

Abstract

This study investigates the factors influencing employee acceptance and actual AI use intensity (frequency and routinization) by integrating the Technology Acceptance Model with organizational and psychosocial variables. Data were collected via an online survey of Romanian Generation Z participants with work experience (N = 272) between 10 May and 25 May 2025, and analyzed using PLS-SEM with a moderated mediation model. Perceived usefulness emerged as the strongest driver of attitude, intention, and AI use intensity. Organizational AI readiness increased perceived usefulness and was positively associated with psychological safety. Trust influenced both intention and AI use intensity and partially mediated the relationship between perceived usefulness and intention. Technostress was negatively associated with attitudes and weakened the positive relationship between psychological safety and perceived ease of use. By shifting the focus from intention to AI use intensity, the study refines acceptance theory for AI-enabled work and clarifies how organizational context, trust, and digital strain shape sustained and routinized AI use in daily work. Practically, the findings suggest that organizations should communicate AI value and task fit, foster psychologically safe learning climates, build trust through transparency and guidance, and actively mitigate technostress through training, workload design, and clear expectations.

Keywords: artificial intelligence (AI); Technology Acceptance Model (TAM); technostress; psychological safety; organizational AI readiness

1. Introduction

Digital transformation and the rapid integration of data-driven and AI-driven solutions have increased interest in understanding why people adopt technology and how they use it at work. Much of the research relies on acceptance models (especially Technology Acceptance Model—TAM and its extensions), which explain how perceived usefulness and perceived ease of use shape attitudes and behavioral intentions [1–3]. However, the literature remains fragmented in three key areas. First, many studies focus on intention to use, treating usage as the final outcome, even though organizations ultimately care about sustained enactment. In this study, we therefore focus on actual AI use, operationalized as AI use intensity—the frequency and routinization of AI use in daily work [4,5], rather than as goal attainment or performance outcomes. Second, organizational context variables that support or constrain adoption (e.g., organizational readiness and support and psychological safety) are often examined separately from core acceptance beliefs, even though

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evidence shows that climate and leadership shape technology-related learning and risk taking [6,7].

Third, employees increasingly make rapid friction-value evaluations when interacting with digital tools, especially AI: they quickly weigh interaction frictions (learning effort, errors, uncertainty, and cognitive load) against perceived immediate value (time saved, output quality, and task fit) when deciding whether to persist and rely on AI outputs. These gaps call for integrated models that include organizational and actual use dimensions.

This study addresses these gaps by testing an integrated model with Generation Z, a group characterized by intensive technology exposure, high digital expectations, and early adoption of AI tools in education and work contexts [8,9]. The model combines TAM beliefs (perceived usefulness and perceived ease of use) with organizational readiness and support, psychological safety, technostress, and trust to explain both acceptance (attitude and intention) and AI use intensity. Trust is theorized as a distinct mechanism because AI use involves uncertainty about output quality, appropriate reliance, and responsibility [10,11]. Technostress is included as a boundary condition because AI-enabled work can intensify information overload and complexity, potentially undermining attitudes and perceived ease of use [12–14].

To clarify the research gap and novelty, prior organizational AI acceptance research often (a) treats intention or generic "use" as the endpoint, leaving the transition from intention to sustained use under-specified, and (b) examines uncertainty-reduction mechanisms (e.g., trust) and strain mechanisms (e.g., technostress) largely in isolation, providing limited insight into how organizations can simultaneously enable reliance on AI while preventing digital strain. Accordingly, this study addresses the following research question: How do core TAM beliefs and HR-relevant organizational conditions jointly explain Generation Z employees' intention to use AI systems and their AI use intensity, and through which mechanisms of trust and technostress is intention translated into frequent and routinized use in daily work? In this study, intention to use reflects motivational readiness to adopt AI, while AI use intensity captures frequent and routinized integration of AI into everyday work activities.

The theoretical contributions are threefold: (1) shifting the focus from intention to actual AI use intensity (frequency and routinization); (2) explicitly connecting organizational conditions (organizational readiness and support and psychological safety) with individual acceptance beliefs; and (3) modeling trust and technostress as, respectively, a key explanatory mechanism and a boundary condition in AI system adoption.

Beyond theory, the paper provides practical contributions for organizations implementing AI systems with early-career employees. Specifically, the results inform how to (a) communicate AI value and task fit in concrete terms, (b) create psychologically safe environments for experimentation and learning, (c) build trust through transparency, usage guidance, and governance, and (d) proactively reduce technostress through training, workload design, and clear expectations about acceptable AI use.

2. Literature Review and Hypotheses Development

The literature on employee acceptance and AI use intensity is based on behavioral models that explain the transition from beliefs and evaluations to intention and usage outcomes. The Technology Acceptance Model (TAM) identifies perceived ease of use and perceived usefulness as central determinants of attitude and intention [1], while later extensions emphasize the importance of social and organizational influences [2,15]. In AI-enabled work, adoption also involves uncertainty about output quality and appropriate reliance, which increases the importance of trust [10,11,16]. Moreover, organizations benefit when AI is used consistently and integrated into everyday work routines, rather than being adopted only superficially or tried occasionally [4,5]. Building on these perspectives, this section develops hypotheses linking TAM beliefs, organizational context, trust, technostress, and AI use intensity. Recent empirical evidence shows that workplace AI can create both resources and demands, shaping productivity and employee well-being [17,18].

To highlight the added value of the proposed model, we distinguish between (i) well-established TAM relationships included as a confirmatory baseline (e.g., perceived ease of use/perceived usefulness → attitude/intention) and (ii) the HRM-oriented extensions central to this study: organizational antecedents (organizational readiness and support and psychological safety) and two complementary mechanisms—trust (uncertainty reduction and willingness to rely on AI outputs) and technostress (resource depletion and digital strain)—that together explain whether intention is converted into sustained AI use intensity.

Perceived ease of use (PEOU) is a core determinant of acceptance in the Technology Acceptance Model (TAM) and related frameworks [1,2]. When a system is perceived as easy to learn and operate, the cognitive effort required to use it decreases, which typically supports a more favorable evaluative stance toward the experience and, consequently, a more positive attitude toward use [1]. Recent cumulative evidence confirms that PEOU remains a consistent antecedent within acceptance mechanisms, including attitude formation: a model-based meta-analysis of TAM studies reports robust support for these relationships [19], and a large-scale meta-analysis (693 studies) similarly indicates systematic effects of perceived ease on attitude, intention, and usage outcomes across contexts [3]. Evidence from emerging AI-related applications (e.g., AI tools and humanoid robots in education) further shows that PEOU significantly predicts attitude and that attitude mediates downstream intention to use [20]. As such, we propose the following hypothesis:

H1. *Perceived ease of use (PEOU) of AI systems positively influences attitude toward using AI systems (Attitude).*

Within TAM, perceived ease of use (PEOU) refers to the extent to which users believe that using a system is effortless, easy to understand, learn, and operate [1]. In addition to lowering the cognitive costs of use, PEOU can strengthen users' sense of control by reducing ambiguity, unexpected errors, and uncertainty during interaction, making the system feel more predictable and, consequently, more trustworthy. Consistent with trust-based extensions of technology acceptance, ease of use can contribute to trust formation by normalizing the experience, improving process understanding, and reducing suspicion associated with complexity or opacity [16]. Empirical findings support this mechanism in digital public services and socio-technical platforms, where PEOU is identified as an antecedent of trust alongside structural assurances, perceived security, and information quality [21], and in online public services, where PEOU is considered a trust-generating factor through reduced learning barriers and uncertainty [22]. Accordingly, we expect PEOU to positively support trust in the system. Thus, we propose the following hypothesis:

H2. *Perceived ease of use (PEOU) of AI systems positively influences trust in AI systems.*

Within TAM, perceived usefulness (PU) refers to the extent to which a user believes that a system enhances performance and provides tangible benefits, such as increased efficiency, higher-quality outputs, and time savings. When a system is considered useful, it is typically evaluated more favorably because it indicates a positive benefit–cost ratio, fostering a more positive attitude toward use [1]. Cumulative evidence supports this relationship: meta-analytic syntheses of TAM-family models consistently identify PU as a stable antecedent of attitudinal evaluations, although effect sizes may vary across contexts and samples [3,19]. Recent findings in emerging technology settings also show that perceiving a technology as relevant and beneficial to one's goals is associated with a more favorable attitude toward its use [20].

Consequently, based on theoretical arguments and empirical results from the literature, we formulate the following hypothesis:

H3. *Perceived usefulness (PU) of AI systems positively influences attitude toward using AI systems (Attitude).*

In technology acceptance research, perceived usefulness (PU) is an instrumental belief: when users expect a technology to improve performance, efficiency, or outcome quality, they are more likely to form a stronger intention to use it. In the classic (TAM), intention largely reflects this anticipated benefit–cost evaluation, where expected gains motivate future use [1]. Extensions such as TAM2 similarly emphasize PU as a stable predictor of intention in organizational settings because it links the system to outcomes that are salient and observable for users [15]. Meta-analytic evidence supports the robustness of this relationship across contexts: syntheses within the TAM family consistently confirm PU's positive effect on intention, even though effect sizes vary by domain and technology type [19], and large-scale reviews likewise identify PU as one of the most consistent determinants of intention relative to other acceptance predictors [3]. Recent studies provide convergent evidence, showing PU as a primary driver of intention in digital health [23] and as a substantial contributor to intention formation in AI-based educational applications, including humanoid robots, through attitudinal and practical value assessments [20]. Overall, clearer perceptions of functional benefits are associated with stronger and more stable intentions to use the system. Accordingly, we propose the following hypothesis:

H4. *Perceived usefulness (PU) of AI systems positively influences intention to use AI systems.*

In technology acceptance models, perceived usefulness (PU) reflects users' cognitive evaluation of a tool's contribution to improved performance or outcomes [1]. When users anticipate tangible benefits, PU provides a rational basis for sustained, goal-directed engagement with the technology. Cumulative evidence supports the relevance of this value-based evaluation for actual use: a large UTAUT meta-analysis shows that performance expectancy (conceptually similar to PU) is strongly associated with use across contexts and technology types [24]. In this study, the behavioral outcome is AI use intensity, reflected in frequency and routinization of AI use in daily work. From this perspective, higher perceived usefulness should be associated with more frequent and routinized AI use. Accordingly, we expect PU to be positively related to AI use intensity in the proposed model. Consequently, we propose the following hypothesis:

H5. *Perceived usefulness (PU) of AI systems positively influences AI use intensity (AI Use Intensity).*

Within TAM, perceived usefulness (PU) reflects the belief that a technology improves performance or provides tangible benefits [1]. Beyond its instrumental role, PU can also support trust formation: when a system is experienced as effective and beneficial, users are more likely to infer competence and predictability, which are central bases of trust in classical frameworks [10,25]. Trust-integrated acceptance models similarly propose that favorable performance evaluations lead to judgments of credibility and reliability [16]. Empirical evidence supports this logic across digital contexts, showing PU as a significant predictor of trust in online services [26] and in digital public services, where usefulness and efficiency reinforce the perceived credibility of the platform [22]. Overall, perceiving a technology as useful reduces uncertainty about its value and functioning and strengthens trust in the system. Consequently, we formulate hypothesis:

H6. *Perceived usefulness (PU) of AI systems is positively associated with trust in AI systems.*

In contemporary TAM extensions, attitude toward use remains a key affective–evaluative construct that summarizes users' overall appraisal of using the technology and channels perceived benefits and effort into willingness to act. When attitude is positive, psychological resistance tends to be lower and intention to use is more likely [27]. Meta-analytic evidence further indicates that incorporating attitude increases explanatory power and that attitude significantly links technology-related beliefs to intention [28], contributing to more stable intentions when evaluations are favorable [28]. Recent empirical research in generative AI contexts supports this relationship: among teachers using generative AI tools for teaching and learning, attitude is a central predictor of behavioral intention to use [29]. In light of the above arguments and evidence, we propose the following hypothesis:

H7. *Attitude toward using AI systems positively influences intention to use AI systems.*

In planned behavior and technology acceptance research, intention represents the most immediate form of motivational readiness to act: stronger intentions typically increase the likelihood of actual use because they reflect a commitment to invest effort and time [30]. Applied to AI use intensity, this means that more frequent and routinized activation of an AI system is more likely when intention to use is high. Meta-analytic and empirical evidence supports this pattern across contexts, with intention predicting usage behavior in health technologies [31] and digital services [32], and recent work suggests that behavioral intention also explains use of AI tools [33]. However, research highlights an intention–behavior gap in contexts where barriers such as limited resources or insufficient support impede enactment [34]. Nonetheless, under typical conditions of access and technical support, the expected relationship between intention and AI use intensity remains positive. Consequently, we propose the following hypothesis:

H8. *Intention to use AI systems positively influences AI use intensity.*

In digital contexts, especially in the use of AI-based systems, the adoption decision is strongly influenced by uncertainty (such as quality of results, possible errors, confidentiality, and consequences of use). Trust serves as a mechanism to reduce this uncertainty: when users perceive the technology as credible, predictable, and "safe," they are more willing to adopt it and incorporate it into their practices [35]. Recent empirical evidence consistently confirms the role of trust as a predictor of intention. For example, studies on the acceptance of conversational and AI solutions show that trust is linked to intention to use both directly and by reducing perceived risk and increasing anticipated benefits [36,37]. At the aggregate level, meta-analyses in digital services with high data sensitivity show that trust has a direct effect on intention, in addition to the established effects of perceived usefulness and ease of use [38]. Recent employee-focused studies also reinforce the centrality of trust in AI: trust mediates key perceptions and acceptance of AI use [39] and influences receptiveness to generative AI advice in complex tasks [40]. Therefore, the following hypothesis is proposed:

H9. *Trust in AI systems positively influences intention to use AI systems.*

While the relationship between trust and intention to use reflects initial readiness to adopt, the literature indicates that the role of trust extends beyond intention. Trust also affects how users actually rely on the system, leading to more frequent, deeper, and more integrated use. Therefore, it is justified to examine a direct effect of trust on actual use as well. When users lack sufficient trust, they tend to limit their use to “safe” functions, over-check, avoid integrating the system into critical tasks, or abandon it quickly. The (X)AI literature highlights that trust and distrust regulate reliance—determining when, how much, and how users depend on the system—and this mechanism is directly reflected in actual use behaviors [11]. Empirically, this link is evident in recent studies: for example, when using an AI chatbot as a nutritional assistant, trust predicted actual use, sometimes even independently of intention [41]. Among students, results show that both intention and trust are directly associated with actual use of ChatGPT, and trust is among the most important predictors of use [42]. At the synthesis level, meta-analytic evidence from digital services shows that trust has a direct effect on use and an indirect effect through intention [38], supporting a positive relationship even when “use” is operationalized through continued-use indicators (e.g., frequency or routinization). Further, recent evidence indicates that different forms of trust can translate into distinct advice-taking behaviors when working with generative AI, highlighting trust as a mechanism linking perceptions to enacted use [40]. Consequently, we propose the following hypothesis:

H10. *Trust in AI systems positively influences AI use intensity (AI Use Intensity).*

In organizational contexts, especially when the use of a technology is expected, AI readiness reflects employees’ perceptions that their organization possesses the strategic orientation, managerial support, and preparedness necessary to implement artificial intelligence effectively. Prior research integrating organizational readiness with TAM shows that perceived organizational readiness positively shapes perceived usefulness by signaling that technological systems are valuable, supported, and relevant for work tasks [43]. Empirical studies in AI contexts further demonstrate that organizational support, strategic alignment, and employee preparedness significantly enhance perceived usefulness of AI by strengthening expectations of performance benefits [44,45]. Accordingly, higher levels of perceived organizational AI readiness are expected to foster stronger perceptions of AI usefulness among employees [46]. At the level of evidence synthesis, review and meta-analysis studies show that social norms and subjective norms consistently emerge as relevant antecedents of central constructs in the TAM family, including perceived usefulness, although the strength of these relationships may vary depending on context and technology type [47]. Additionally, recent syntheses on technology acceptance in education highlight the consistent role of organizational culture, leadership, and social influences in shaping TAM-type beliefs, reinforcing the expectation of a positive relationship between organizational readiness and support and perceived usefulness [48]. Therefore, we propose the following hypothesis:

H11. *Organizational AI readiness positively influences the perceived usefulness of AI systems.*

Conceptually, psychological safety refers to the perception that it is “okay” to take interpersonal risks at work (e.g., asking questions, reporting problems, admitting errors) without fear of social or professional sanction [6]. In contexts of change, including technological implementations, this state becomes critical because employees must experiment, learn quickly, and frequently communicate difficulties or ambiguities. The literature consistently shows that organizational factors, such as management practices, climate, supportive or encouraging signals, and employee voice norms, are relevant antecedents of psychological safety. A major meta-analysis highlights the role of organizational context and perceived support in fostering psychological safety, with subsequent effects on learning behaviors and performance [7]. Similarly, a recent extensive review shows that psychological safety is strongly anchored in the conditions created by the organization (policies, practices, leadership), especially in environments characterized by uncertainty and change [49,50]. From this perspective, organizational AI readiness refers to a set of signals indicating that AI adoption is strategically supported, carefully planned, and accompanied by managerial involvement and employee preparedness. Prior research on AI and digital transformation shows that when organizations provide clear strategic direction, visible managerial support, and resources for adaptation, employees experience less uncertainty and anxiety, contributing to a psychologically safer environment during AI-related change [46,51]. Unlike organizational pressure, which emphasizes compliance and normative expectations, organizational AI readiness serves as a supportive and enabling context by reducing fear of failure and encouraging voice behavior, thereby strengthening psychological safety during technological transitions [45,52]. When the organization conveys that change is a priority, provides benchmarks, and encourages involvement, employees may interpret the context as one in which it is permissible to discuss problems and ask for help. Convergent empirical studies from different organizational contexts show positive associations between organizational support or involvement and psychological safety, suggesting that organizational signals substantially influence how safe people feel to express themselves [53,54]. Therefore, to reflect the theoretical mechanism described above, we formulate the following hypothesis:

H12. *Organizational AI readiness is positively associated with psychological safety.*

In TAM logic, perceived ease of use (PEOU) reflects the extent to which the user considers using a system to be "effortless" [1]. Psychological safety, in turn, describes a climate in which people feel safe to take interpersonal risks (e.g., asking questions, admitting they do not know, reporting errors) without fear of sanctions or ridicule [6]. In such an environment, learning behaviors (help-seeking, feedback-seeking, experimentation) tend to increase, reducing anxiety related to "making mistakes" and accelerating the process of adapting to new technologies; as a result, the technology is experienced as easier to use. Syntheses and meta-analyses in the psychological safety literature consistently support the idea that psychological safety facilitates learning and adaptation in contexts of change by increasing open communication and proactive behaviors [7,49,55]. The connection with PEOU is also directly addressed in the technology adoption literature: research on the adoption of collaborative technologies shows that psychological safety is associated with more favorable perceptions of ease of use, partly by reducing social inhibitions ("I do not make a fool of myself if I do not succeed") and by encouraging mutual support in the learning process. A relevant example demonstrates that psychological safety has a positive effect on PEOU, which (together with perceived usefulness) partially mediates actual technology use [56]. More recently, in digital collaboration contexts (virtual teams), psychological safety is associated with effort expectancy (the conceptual equivalent of PEOU), indicating that when people feel safe to ask for help and experiment, they perceive team technologies as easier to use [57]. Similarly, recent studies on AI tools in education indicate that a climate of safety and confidence in use supports the perception of reduced effort (i.e., ease of use/effort expectancy) and, through this, the willingness to integrate the technology [58]. Therefore, in accordance with the proposed model, we formulate hypothesis H13 as follows:

H13. *Psychological safety positively influences the perceived ease of use of AI systems.*

Trust and technostress are modeled together because they capture two complementary HR-relevant mechanisms that shape the transition from intention to sustained AI use intensity. Trust represents uncertainty reduction and the willingness to rely on AI outputs when consequences are ambiguous, while technostress reflects resource depletion and strain triggered by overload, complexity, or invasion. In practice, employees may perceive AI as useful and become willing to rely on it, yet still experience digital strain that undermines evaluative acceptance and learning. Modeling both mechanisms thus provides a more complete explanation of when organizational resources (e.g., psychological safety) and individual beliefs translate into frequent and routinized AI use.

Recent literature defines technostress as a stress reaction caused by the demands associated with using digital technologies (e.g., overload, invasion of personal time, complexity, insecurity, or uncertainty). This type of stress is relevant to the attitudinal component because, through affective and cognitive mechanisms, it tends to amplify negative emotions (anxiety, frustration, exhaustion) and reduce positive states, thereby shifting the overall evaluation of technology in a more unfavorable direction [14]. Beyond the mechanistic argument, there is direct empirical support for the link between technostress and attitudes. For example, a study of adult samples found that higher levels of technostress are associated with more negative attitudes toward digital transformation, with the effect being significant and negative [59]. Similarly, research in the educational field shows that technostress negatively affects users' attitudes toward technology use (for example, among teachers using mobile technologies), suggesting that the pressure and discomfort experienced when interacting with technology lead to less favorable attitudinal evaluations [60]. Recent research extends technostress to generative AI settings by identifying GenAI-specific stressors and their manifestations among young professionals [61]. Empirical evidence also suggests AI technostress relates to exhaustion, work–family conflict, and reduced job satisfaction [17], and can simultaneously hinder or foster career growth via distinct stress pathways [62]. Accordingly, we propose the following hypothesis:

H14. *Technostress related to AI use negatively influences attitude toward using AI systems.*

In addition to direct relationships between constructs, models of technology adoption and use are often refined through moderation effects to capture the idea that the same predictor does not operate uniformly across conditions. Moderation occurs when the influence of an independent variable on a dependent variable depends on the level of a third variable (moderator), indicating a conditional effect [63]. Thus, it is logical to assume that psychological safety provides a relational context that makes learning and experimenting with technology easier, but this resource does not operate in a vacuum. Psychological safety describes a climate in which people feel comfortable asking questions, seeking help, and admitting difficulties without fear of negative consequences [6]. In such a climate, learning behaviors and feedback sharing are enhanced, which plausibly reduces the effort required to interact with technology and increases Perceived Ease of Use [49]. At the cumulative level, meta-analytic evidence shows that psychological safety has robust links to learning behaviors and effective functioning in organizational contexts, suggesting a mechanism by which users perceive processes (including technological ones) as more approachable and less cognitively demanding [7]. At the same time, technostress functions as a pressure specific to digital environments, associated with overload, complexity, invasion of personal time, uncertainty, and feelings of inadequacy. Viewed through the lens of the Job Demands-Resources model (JD-R), technostress is often conceptualized as a job demand that consumes cognitive and emotional resources and can alter technology-related evaluations [64,65]. Moreover, empirical results explicitly show that, in digital educational contexts, increased use of technologies can amplify technostress, which then reduces the perception of ease of use [66]. In other words, when technological stress is high, users tend to perceive technology as more difficult, more demanding, and less intuitive. From

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this, the following moderation logically derives: even if psychological safety encourages people to ask, experiment, and learn, a high level of technostress can erode the ability to capitalize on these benefits through overload and resource depletion. This idea is directly supported by the Conservation of Resources theory (COR), which argues that stressors can consume available resources and change the way individuals capitalize on contextual resources [67,68]. Recent research shows that techno-stressors interact with psychological safety: certain dimensions (e.g., techno-invasion) can diminish the benefits of a safe climate by draining resources, making the effects of psychological safety contingent on the level of technological stressors [69]. Similarly, the literature on inhibitors of technostress frequently treats organizational conditions (support, facilitation, encouragement of experimentation) as variables that alter the intensity of the negative effects of technological stressors, reinforcing the idea that relationships around technology are often context-dependent [70]. Therefore, we formulate hypothesis H15 as follows:

H15. *Technostress moderates the relationship between psychological safety and perceived ease of use of AI systems, such that the effect of psychological safety on PEOU is weaker at high levels of technostress.*

Taken together, the proposed model describes a sequential mechanism in which organizational AI readiness serves as an upstream HR signal that shapes both outcome expectations (perceived usefulness) and the learning climate (psychological safety). Psychological safety then supports experimentation and learning, which reduces perceived frictions and increases perceived ease of use. These acceptance beliefs inform attitude and trust, which together strengthen the intention to use AI at work. Intention is expected to lead to AI use intensity (frequent and routinized AI use), while technostress acts as a strain mechanism that undermines favorable evaluations (via attitude) and weakens the extent to which psychological safety leads to low-friction experiences (i.e., a moderation effect).

To more accurately capture the psychological mechanisms behind technology adoption, direct relationships can be complemented by mediation relationships. The central idea is that some variables do not influence intention directly, but exert their effect through an intermediary process, usually an affective-cognitive evaluation such as attitude.

The literature on technostress indicates that technological demands, such as overload, complexity, intrusion, and uncertainty, tend to generate negative affective states and cognitive costs, including frustration, fatigue, and anxiety, which lead to a less favorable overall evaluation of the technology [13]. Consistent with hypothesis H14, technostress reduces the likelihood that users will develop a positive attitude toward use, as their experience with technology is associated with effort, tension, and perceived risk. At the same time, the Attitude → Intention to Use relationship (H7) is one of the most stable links in the TAM model: when users have a more favorable attitude toward use, their intention to use the technology increases. Recent meta-syntheses confirm the role of attitude as a proximal determinant of intention in acceptance models [28]. Combining these two relationships, an indirect effect logically follows: technostress decreases intention to use by deteriorating attitude. This sequence is also supported empirically: a study on teachers shows that technostress negatively affects attitude toward technology, and attitude positively influences intention to continue using it. Consequently, a significant part of the impact of technostress is transmitted to intention through attitude [60]. In AI-enabled work, such strains are increasingly linked to well-being outcomes, where AI-related demands (e.g., technostress) can impair satisfaction and work–life balance, while AI-related resources can offset negative effects [17,18]. Therefore, we formulate the mediation hypothesis:

H16. *Technostress related to AI use negatively influences intention to use AI systems through attitude (Technostress → Attitude → Intention to Use).*

According to the TAM framework, perceived ease of use reduces the cognitive costs of interaction (such as effort, learning time, and probability of error) and increases the sense of control, which typically leads to a more favorable evaluation of use, that is a positive attitude toward the technology [1]. As previously discussed in H7, attitude remains a proximal determinant of intention: when users develop a favorable disposition toward use, their intention to use the technology becomes stronger and more stable [28]. In current applications of TAM in emerging contexts (e.g., generative artificial intelligence tools), attitude is retained in the model specifically to capture the shift from perceiving a technology as "easy" to deciding "I will use it" [29]. Accordingly, we propose the following mediation hypothesis:

H17. *Perceived ease of use of AI systems has a positive effect on intention to use AI systems through attitude (Perceived Ease of Use → Attitude → Intention to Use).*

If mediation mechanisms clarify the path by which an explanatory variable influences intention or behavior, it is plausible in the present model that cognitive assessments of the value of the technology do not automatically translate into intention, but are "converted" through a psychological mechanism of uncertainty reduction, namely, trust.

For the relationship Perceived Usefulness → Trust, the argument follows the logic of hypothesis H6: when users perceive the technology as useful (producing results, increasing efficiency, supporting performance), this usefulness can serve as an indicator of the system's competence and reliability, thereby reinforcing trust. In models that integrate trust with technology acceptance, trust is treated as a critical determinant in digital contexts where users cannot fully assess quality "from the inside" and must rely on signals of performance and predictability [16]. For the Trust → Intention to Use relationship, hypothesis H9 states that trust reduces perceptions of risk and uncertainty and increases willingness to adopt. In this context, perceived usefulness can increase intention not only directly (as captured in H4), but also indirectly, by strengthening trust, which then fuels the intention to use. Empirically, this sequence has been explicitly tested: in a study on mobile wallet adoption, trust mediated the influence of perceived usefulness on intention to use [71]. Similarly, recent research in public digital services positions trust as a central mechanism through which perceived usefulness is transferred to the intention to continue or use, confirming its role as a "bridge" between value assessment and behavioral decision [72]. In high-stakes AI contexts, trust also appears as a mediator between performance expectations (a construct closely related to perceived usefulness) and behavioral intention, further supporting the generality of the proposed mechanism [73]. Consequently, the following mediation hypothesis is formulated:

H18. *Perceived usefulness (PU) of AI systems positively influences intention to use AI systems through trust (PU → Trust → Intention to Use).*

Another proximal mechanism in mediating relationships is intention, which translates psychological evaluations and dispositions into concrete usage decisions [30]. In this framework, attitude reflects the overall evaluation (favorable or unfavorable) toward usage, while usage intention captures the commitment and immediate readiness to act. According to established behavioral logic, intention is the closest antecedent of behavior, and attitude tends to fuel intention by valuing benefits and reducing psychological resistance to usage [30]. Recent research across different technological fields empirically supports the attitude → intention relationship [74]. Furthermore, for usage to be effective, occasional use is insufficient; goal-oriented use that produces results and supports the achievement of the objectives for which the system is adopted is important. Conceptually, this distinction is captured by the shift from "use" to AI use intensity, reflected by frequent and routine AI use in daily work. Recent empirical evidence also supports that intention has a strong predictive role for usage behaviors and decisions in diverse technological contexts [75] and may be a critical determinant of effective adoption [76]. Therefore, if H7 and H8 (previously argued) indicate that attitude drives intention and intention supports frequent and routinized use, it is coherent to expect that intention to use functions as the mechanism through which attitude translates into frequent and routinized use. Thus, the following mediation hypothesis can be formulated:

H19. *The relationship between attitude toward using AI systems and AI use intensity is positively mediated by intention to use (Attitude → Intention to Use → AI Use Intensity).*

In light of the foregoing discussion, we propose the following comprehensive research framework (Figure 1):

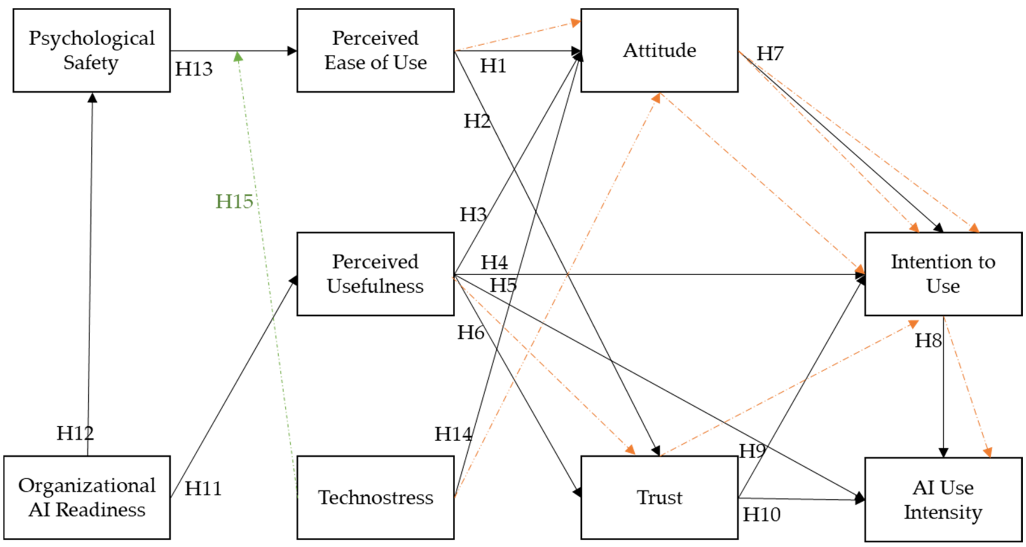

Figure 1. Proposed research model. Bold lines are hypotheses. Orange dashed lines indicate the mediating role (H16–H19). Green dashed line indicates the moderating role (H15).

3. Methods

3.1. Measurements

To address the limitations of single-item measures, this study used pre-validated multi-item scales, which were slightly rephrased to fit the present research context [77,78]. Data were collected through an online survey consisting of 42 items, primarily measuring nine constructs as shown in Figure 1. Thirty-four items measured perceived ease of use (three items), perceived usefulness (three items), attitude (two items), psychological safety (six items), trust (five items), technostress (five items), organizational AI readiness (six items), intention to use (two items), and AI use intensity (two items). All constructs were operationalized as reflective measurement models, consistent with previous PLS-SEM research [79], and their items were measured using a five-point Likert scale (1 = strongly disagree to 5 = strongly agree). In addition to these constructs, one question measured the frequency of AI technology usage by Gen Z in their current job, using a five-point Likert scale (1 = very rarely to 5 = very frequently). Finally, seven socio-demographic variables were included: gender, age, highest level of education completed, monthly personal income, occupational field (industry/sector of employment), average number of working hours per week, and employment status (e.g., full-time, part-time, self-employed).

The choice of the PLS-SEM methodology is further supported by the study's clear emphasis on prediction and outcome-driven explanation. The proposed model aims to forecast Generation Z employees' AI use intensity as the primary behavioral outcome, rather than merely explaining adoption intentions. Additionally, PLS-SEM is suitable for predictive research and when the main objective is to maximize the explained variance of key endogenous constructs [79]. The structural model is complex, as it includes both mediation and moderation relationships. This indicates that variance-based estimation is preferable to covariance-based methods, particularly when the data are non- normal and the sample size is moderate [79,80]. Finally, focusing on frequent and routinized use as a key outcome variable aligns with recent methodological recommendations that PLS-SEM is appropriate for modelling behavioral outcomes and goal-oriented use constructs in organizational technology research [81].

Several constructs (Attitude, Intention to Use, and AI Use Intensity) were operationalized with two reflective indicators. While the three-indicator rule is a common guideline in covariance-based confirmatory factor models, it is not a strict requirement in PLS-SEM. According to PLS-SEM guidance, two-indicator reflective measures can be retained when constructs are conceptually narrow, the indicators are well-established in prior research, and they display strong and similar loadings [79,80]. In our data, both items for these constructs showed very high loadings, and the constructs met recommended thresholds for composite reliability and convergent validity, supporting stable estimation. Model identification was further supported because all reflective constructs in the model had at least two indicators, and the PLS algorithm converged without estimation issues.

Regarding AI Use Intensity, the two indicators capture (i) frequency of AI use and (ii) routine integration of AI into daily work. In survey-based acceptance research, such sustained and routine integration is often treated as an observable manifestation of continued use. However, these self-reports do not directly measure task goal attainment or performance outcomes; future research should complement perceptual measures with objective usage logs and task-level outcome indicators.

The measurement items for the constructs in this study were adapted from well-established theoretical frameworks and prior empirical research in organizational and technology acceptance literature, as shown in Table 1. Psychological safety was measured using items derived from research that conceptualizes it as a shared perception of interpersonal risk tolerance and support for learning, experimentation, and open communication in organizational settings [6,55]. Perceived usefulness and perceived ease of use were operationalized based on the Technology Acceptance Model, which emphasizes users' beliefs about the performance-enhancing value of a technology and the effort required to use it effectively [1], as well as subsequent extensions that highlight the role of organizational and social influences in shaping these perceptions [2,15]. Attitude toward use and intention to use were measured in line with behavioral acceptance research, where attitude reflects users' overall evaluative stance toward technology use and intention represents the most immediate motivational antecedent of behavior [1,30]. AI Use Intensity was measured using two indicators capturing frequency and routinization of AI use in daily work. Trust was measured following established work on trust in information systems, which defines it as users' confidence in the reliability, competence, and predictability of technology under conditions of uncertainty [10,16]. Finally, technostress and organizational AI readiness were operationalized using items adapted from research on technology-related demands and social influence in organizations, which emphasize the impact of cognitive overload, per-

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ceived threat, managerial expectations, and normative pressures on employees' responses to technological change [12,15,44,45,47,82,83].

Table 1. Latent variables and items.

Latent Variables	Code	Items	Adapted from
Attitude	AT1	I have a positive attitude toward using AI technologies in my work.	[1,2,28,30]
	AT2	I believe that the use of AI in our organization is a good idea.	
Organizational AI Readiness	OR1	I believe that my organization must adopt artificial intelligence technologies to remain competitive.	[43–45,47,48]
	OR2	The organization's strategy for implementing AI is well-designed and appropriate to my needs.	
	OR3	I expect that the use of AI will bring personal benefits to me.	
	OR4	The management actively supports the transition toward AI adoption in my organization.	
	OR5	I consider that AI will contribute to the long-term success of my organization.	
	OR6	I feel prepared to adapt to the changes brought about by the implementation of AI.	
Perceived Ease of Use	EU1	It is easy for me to learn how to use artificial intelligence technologies in my work.	[1,2,19,20]
	EU2	My interaction with artificial intelligence technologies is clear and understandable.	
	EU3	I find it easy to control artificial intelligence technologies to perform the tasks I want.	
Perceived Usefulness	PU1	Using artificial intelligence technologies in my work allows me to complete tasks more quickly.	[1,15,19]
	PU2	Artificial intelligence technologies improve the quality of my work.	
	PU3	Artificial intelligence technologies help me achieve better performance/results in my job.	
Psychological Safety	PS1	I feel comfortable asking questions about the use of AI in our organization without fear of being judged.	[6,7,49,55]
	PS2	I can express concerns about the impact of AI on my job without fear of negative consequences.	
	PS3	My team actively encourages collaboration and the exchange of ideas to improve AI usage.	
	PS4	I feel valued and respected when I contribute suggestions regarding AI implementation.	
	PS5	I believe that mistakes related to the use of AI are treated as learning opportunities rather than grounds for punishment.	
	PS6	Management fosters an environment in which I can openly discuss the challenges associated with AI.	

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Table 1. *Cont.*

Latent Variables	Code	Items	Adapted from
Technostress	TS1	I feel overwhelmed by the amount of information or tasks generated by artificial intelligence technologies.	[12,14,82,83]
	TS2	I am afraid that AI could replace certain aspects of my job.	
	TS3	The complexity of AI systems creates difficulties in my day-to-day work.	
	TS4	Using AI makes me feel that I have less control over my work.	
	TS5	The time required to learn artificial intelligence technologies reduces my productivity.	
Trust	TR1	I trust that the artificial intelligence technologies used in our organization deliver accurate and reliable results.	[10,11,16,25]
	TR2	I trust that the AI technologies are safe and adequately protect the confidentiality of my personal data.	
	TR3	I clearly understand how the artificial intelligence technologies used in our organization function.	
	TR4	I trust that artificial intelligence technologies are employed ethically within our organization.	
	TR5	I trust that I can rely on the artificial intelligence technologies to perform my tasks without major errors.	
Intention to Use	IU1	I intend to use artificial intelligence technologies in my work whenever possible.	[1,2,29,30]
	IU2	I would recommend the use of artificial intelligence technologies to my colleagues in their daily tasks.	
AI Use Intensity	UI1	I frequently use artificial intelligence technologies to perform my work tasks.	[4,5]
	UI2	Artificial intelligence technologies are an integral part of my daily work routine.	

All items are measured on a Likert scale of 1–5: 1 = strongly disagree, 5 = strongly agree. Source: own computation.

Although the questionnaire was administered entirely in Romanian to all participants, an English translation of the instrument was later produced solely for reporting and presenting the results in this publication. No English version was used during data collection. Informed consent was obtained at the beginning of the survey after respondents were informed of the study's purpose, procedures, voluntary participation, and their right to withdraw at any time. Respondents' rights, including anonymity, confidentiality, and privacy, were strictly protected throughout all stages of data collection.

3.2. Data Collection

The target population consisted of Romanian members of Generation Z who had reached legal adulthood (i.e., 18 years of age or older, in accordance with Romanian legislation) and were actively participating in the labor market. This included individuals currently employed on a permanent or temporary basis, self-employed as freelancers, or those who had completed at least one internship while pursuing formal education.

Generation Z was selected as the target population because it is considered the first truly digital-native generation [84], having grown up surrounded by technology [85] and offering a unique perspective on automation, innovation, and work in modern companies [9]. Their constant exposure to digital tools makes them more familiar with and adaptable to technology and AI use in the workplace [86]. However, their attitudes toward AI are mixed. On one hand, they recognize its benefits for efficiency and innovation; on the other, they remain cautious about ethical and trust issues [87]. As they enter the workforce in increasing numbers, understanding their perceptions is essential for organizations seeking to integrate AI responsibly and align technological adoption with employee values [8].

The questionnaire was developed and administered using Google Forms and distributed online between 10 May and 25 May 2025. Participants were initially recruited from undergraduate and master's programs at a well-established higher education institution in Romania. A snowball sampling approach was used to increase sample diversity and achieve a structure that more closely reflects the target population [88,89]. The first respondents were asked to suggest and invite other eligible members of Generation Z from different socio-demographic groups to participate. After screening the data [90], the final sample comprised 272 respondents (Table 2).

Table 2. The sample structure.

Demographic Attributes		Number of Respondents	Percent
Age	18–21 years	151	55.5
	22–25 years	81	29.8
	26–28 years	40	14.7
Gender	Male	130	47.8
	Female	142	52.2
Education	Lower secondary education	1	0.4
	Upper secondary education	129	47.4
	Bachelor's degree	114	41.9
	Master's degree	27	9.9
	Doctoral degree	1	0.4
Monthly net individual income	<2000 RON	66	24.3
	2000–4000 RON	111	40.8
	4000–8000 RON	79	29
	>8000 RON	16	5.9
Employment contract type	Part-time	92	33.8
	Full-time	120	44.1
	Freelance	25	9.2
	Internship	26	9.6
	Other	9	3.3
Field of employment	IT/Technology	39	14.3
	Marketing/Sales	97	35.7
	Finance/Accounting	52	19.1
	Hospitality/Tourism	44	16.2
	Other	40	14.7

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Table 2. *Cont.*

Demographic Attributes		Number of Respondents	Percent
Number of hours worked per week	<10 h	50	18.4
	10–20 h	66	24.3
	21–30 h	36	13.2
	31–40 h	75	27.6
	>40 h	45	16.5

Source: Developed by the authors.

The study sample consisted of a diverse group of young Romanians from Generation Z (18–28 years old), with a balanced gender distribution and varying levels of education, professional experience, and income. Most participants were from fields such as marketing/sales, finance, and hospitality/tourism, and held entry-level or junior positions with net monthly incomes between 2000 and 8000 RON.

4. Data Analysis and Results

4.1. Measurement Model

This study used partial least squares structural equation modeling (PLS-SEM) with 5000 bootstrap resamples, a two-tailed test, and a 95% confidence level—a variance-based methodology particularly effective for predictive research models and complex structural relationships [79]—to investigate the proposed relationships among the constructs. The software used was SmartPLS 4.0 [91], which enables robust estimation despite non-normal data distributions and limited sample sizes.

Regarding the frequently cited three-indicator rule, the measurement model includes three reflective constructs, each with two indicators. In PLS-SEM, this specification is acceptable when reliability and convergent validity are satisfactory and indicator loadings are high. As justified in the Methods section, the two-item constructs met all reliability and validity criteria and did not produce estimation or collinearity problems.

For factor loading thresholds, a loading greater than 0.7 is recommended [79]. Although the outer loadings of indicators PS2 (0.620) and TS1 (0.691) are slightly below the ideal threshold, a loading above 0.6 is considered adequate if other items have high loading scores to support average variance extracted (AVE) and composite reliability (CR), provided that overall construct reliability and validity remain satisfactory [79,92,93]. Established methodological guidelines for PLS-SEM emphasize that indicator loadings are rules of thumb rather than strict cutoffs, and that removal decisions must consider theoretical meaning and content validity alongside statistical criteria [80,94]. In line with these recommendations, although two indicators exhibit loadings slightly below 0.7, they were retained because they reflect a theoretically essential aspect of the construct and appear in validated prior research. Decisions regarding measurement model specification must account for content validity concerns, since modifying indicator sets without theoretical justification may compromise the conceptual integrity of the construct [80]. The outer loadings of all other indicators associated with the latent variables exceeded the threshold recommended in the literature, as presented in Table 3.

Table 3. Reliability and validity measures.

Latent Variable	Factor Loadings	Cronbach's Alpha	Composite Reliability	rho_A	AVE
Attitude	AT1 = 0.939 AT2 = 0.944	0.872	0.940	0.873	0.886
Organizational AI Readiness	OR1 = 0.805 OR2 = 0.772 OR3 = 0.809 OR4 = 0.726 OR5 = 0.841 OR6 = 0.811	0.883	0.945	0.889	0.632
Perceived Ease of Use	EU1 = 0.844 EU2 = 0.860 EU3 = 0.864	0.818	0.943	0.818	0.733
Perceived Usefulness	PU1 = 0.880 PU2 = 0.912 PU3 = 0.921	0.889	0.911	0.890	0.818
Psychological Safety	PS1 = 0.752 PS2 = 0.620 PS3 = 0.793 PS4 = 0.755 PS5 = 0.738 PS6 = 0.776	0.834	0.892	0.841	0.549
Technostress	TS1 = 0.691 TS2 = 0.806 TS3 = 0.821 TS4 = 0.844 TS5 = 0.808	0.869	0.931	0.881	0.633
Trust	TR1 = 0.833 TR2 = 0.809 TR3 = 0.728 TR4 = 0.811 TR5 = 0.857	0.867	0.879	0.877	0.654
Intention to Use	IU1 = 0.944 IU2 = 0.945	0.880	0.896	0.880	0.893
AI Use Intensity	UI1 = 0.947 UI2 = 0.946	0.883	0.904	0.883	0.895

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

Because indicators with slightly lower loadings contribute less to the latent variable score, their inclusion is unlikely to dominate the interpretation of psychological safety and technostress in the structural model. We retained these items to preserve content validity and interpret the corresponding constructs as broad perceptions rather than narrowly defined single facets, while placing greater interpretive emphasis on the overall construct-level relationships.

Construct reliability was assessed using Cronbach's alpha, composite reliability (CR), and rho_A. These indicators evaluate the internal consistency of the measurement items and their ability to represent the same latent construct. Reliability coefficients above the accepted threshold of 0.70 indicate adequate internal consistency [94,95]. As shown in Table 3, all constructs meet this criterion, confirming their stability and reliability. Construct validity was evaluated through convergent and discriminant validity, which together indicate how well the measurement model represents the theoretical constructs. Convergent validity assesses whether indicators measuring the same construct are strongly correlated [90] and is determined through factor loadings and average variance extracted (AVE). According to methodological guidelines, loadings should exceed 0.70 [94], and AVE values should be above 0.50 to indicate sufficient shared variance [90]. As presented in Table 3, all indicators meet these conditions, providing strong support for convergent validity.

Discriminant validity refers to the extent to which a construct is distinct from other constructs, indicating that it does not strongly correlate with measures intended to represent different concepts [90]. The primary method for assessing discriminant validity is the Heterotrait–Monotrait Ratio (HTMT), with a conservative threshold of 0.85 and 0.90 for conceptually similar constructs [79]. As shown in Table 4 and following the recommendations from previous research [79], discriminant validity was assessed using the HTMT in combination with bootstrapped confidence intervals, rather than relying solely on fixed cut-off values. Although the HTMT value between Attitude and Intention to Use slightly exceeds the threshold of 0.90, these constructs, which pertain to the social sciences, are conceptually closely related and may therefore yield higher HTMT values. Importantly, the 95% bootstrap confidence interval does not include the value of 1, indicating that discriminant validity is empirically supported. According to previous research [79], this result suggests that discriminant validity cannot be rejected. Similarly, the HTMT value between Perceived Usefulness and Attitude is slightly above the conservative threshold of 0.85, further supporting discriminant validity.

Although the HTMT criterion is considered more sensitive for detecting potential discriminant validity issues, some authors [79] emphasize that its results should be interpreted alongside inferential testing and other established criteria, such as the Fornell-Larcker criterion. According to Table 5, the Fornell-Larcker criterion [96] was fully satisfied, as the square roots of the AVE for all constructs exceeded their inter-construct correlations. Taken together, these results provide sufficient evidence of discriminant validity, particularly in the context of conceptually related constructs commonly examined in social science research.

Although Organizational AI Readiness is conceptually related to downstream constructs such as psychological safety and perceived usefulness, it captures organizational-level structural and strategic conditions, whereas psychological safety reflects the interpersonal climate for risk-taking and learning, and perceived usefulness reflects individual performance evaluations. Discriminant validity analyses (HTMT and Fornell–Larcker) confirm that these constructs are empirically distinct.

Although some items included in Organizational AI Readiness (such as perceived personal benefits or readiness to change related to AI) may appear conceptually similar to perceived usefulness or personal-level beliefs, they were theorized at the organizational level rather than at the individual level. Organizational AI Readiness reflects employees' perceptions of strategic orientation, managerial support, and institutional readiness to implement AI, whereas Perceived Usefulness represents an individual instrumental assessment of AI's influence on task performance.

Table 4. Discriminant validity—Heterotrait–monotrait ratio (HTMT).

	Attitude	AI Use Intensity	Intention to Use	Organizational AI Readiness	Perceived Ease of Use	Perceived Usefulness	Psychological Safety	Technostress	Trust	Technostress × Psychological Safety
Attitude										
AI Use Intensity	0.766									
Intention to Use	0.925	0.850								
Organizational AI Readiness	0.717	0.683	0.694							
Perceived Ease of Use	0.695	0.613	0.702	0.579						
Perceived Usefulness	0.856	0.798	0.803	0.704	0.689					
Psychological Safety	0.532	0.438	0.449	0.696	0.568	0.494				
Technostress	0.124	0.075	0.075	0.103	0.062	0.094	0.104			
Trust	0.758	0.761	0.754	0.693	0.718	0.670	0.549	0.119		
Technostress × Psychological Safety	0.169	0.183	0.172	0.195	0.220	0.167	0.051	0.288	0.194	

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

Table 5. Discriminant validity—Fornell–Larcker criterion.

	Attitude	AI Use Intensity	Intention to Use	Organizational AI Readiness	Perceived Ease of Use	Perceived Usefulness	Psychological Safety	Technostress	Trust
Attitude	0.941								
AI Use Intensity	0.673	0.946							
Intention to Use	0.810	0.749	0.945						
Organizational AI Readiness	0.634	0.603	0.616	0.795					
Perceived Ease of Use	0.588	0.522	0.596	0.495	0.856				
Perceived Usefulness	0.753	0.707	0.710	0.630	0.588	0.905			
Psychological Safety	0.462	0.385	0.392	0.605	0.468	0.430	0.741		
Technostress	−0.142	0.036	−0.066	0.013	−0.048	0.030	−0.046	0.796	
Trust	0.665	0.675	0.665	0.610	0.599	0.597	0.469	−0.031	0.809

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

Empirically, discriminant validity was supported by HTMT analysis, bootstrapped confidence intervals, and the Fornell-Larcker criterion was met. The inter-construct correlation between Organizational AI Readiness and Perceived Usefulness (0.630; see Table 5) is below the critical threshold for construct redundancy, indicating that these are related but statistically independent constructs.

Variance inflation factors (VIF) were used to assess indicator-level collinearity. Therefore, VIF values of 5 or higher indicate serious collinearity problems, while values around 3 may warrant further examination but do not necessarily indicate serious issues [79,97,98]. In this study, all VIF values were below the critical threshold of 3, and only one indicator (PU3) had a VIF slightly above 3 (VIF = 3.049). Given the theoretical relevance of this indicator and the absence of additional collinearity symptoms, these results do not indicate problematic collinearity.

Finally, because the study relied on cross-sectional self-reported data, potential common method bias was assessed using the full collinearity approach recommended for PLS-SEM [99]. All latent variable VIF values were below the conservative threshold of 3.3, indicating that common method variance is unlikely to substantially bias the structural relationships. Together with the established discriminant validity (HTMT and Fornell–Larcker), these results provide additional reassurance regarding measurement quality.

4.2. Results

The structural model illustrates the relationships (paths) between constructs in the proposed study model (Figure 2). The coefficients of determination (R^2) indicate that the model demonstrates overall satisfactory to strong explanatory power across the endogenous constructs. The explained variance ranges from a minimum of 0.251 for Perceived Ease of Use to a maximum of 0.700 for Intention to Use. Constructs central to behavioral outcomes, such as Attitude (R^2 = 0.622), Intention to Use (R^2 = 0.700), and AI Use Intensity (R^2 = 0.656), show high levels of explained variance, indicating that the proposed predictors account for a substantial portion of the decision-making and usage processes related to AI in the workplace. In contrast, constructs such as Psychological Safety (R^2 = 0.366), Perceived Usefulness (R^2 = 0.397), and Perceived Ease of Use (R^2 = 0.251) exhibit moderate explanatory power, which aligns with their more distal position in the model and their dependence on additional individual and organizational factors not explicitly included. Overall, the observed R^2 values fall within acceptable to strong ranges for PLS-SEM research, indicating that the model is correctly specified and empirically robust.

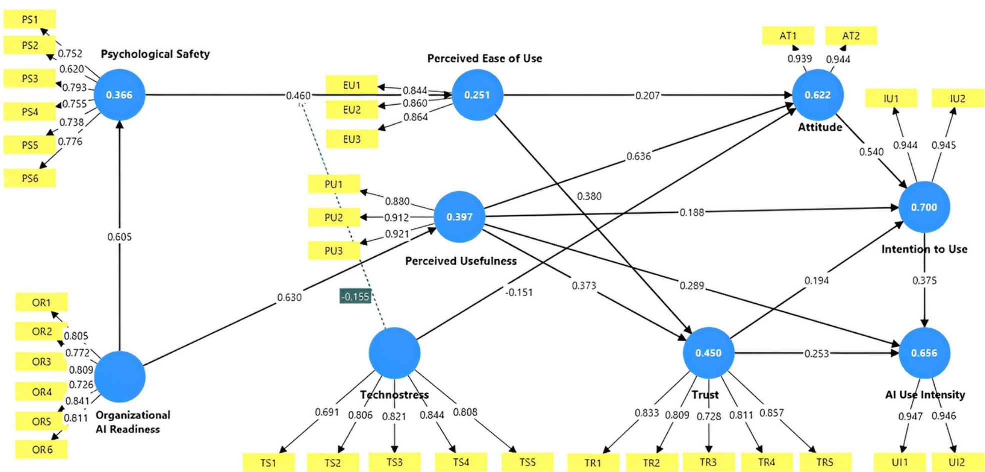

Figure 2. The resulted structural model.

H1 proposed that perceived ease of use positively influences attitude toward use. The results support this hypothesis, revealing a positive and statistically significant relationship between perceived ease of use and attitude (β = 0.207, $p < 0.001$). When artificial intelligence technologies are perceived as easy to learn and operate in work-related tasks, users are more likely to develop a favorable attitude toward their use. Additionally, perceived ease of use is found to positively influence trust (β = 0.380, $p < 0.001$), supporting H2. This indicates that when AI systems are easy to understand and operate in work settings, users are more likely to trust them, as simplicity reduces uncertainty and increases confidence in how these tools function during task execution.

H3 posited that perceived usefulness positively influences attitude toward use. The findings strongly support this hypothesis, as perceived usefulness has a substantial positive effect on attitude (β = 0.636, $p < 0.001$). Among the antecedents of attitude, perceived usefulness is the strongest predictor, highlighting the central role of performance-related evaluations in shaping affective responses to AI. This suggests that when employees find AI genuinely helpful for improving work outcomes, efficiency, or task quality, they are more likely to develop positive attitudes toward its use. Consistent with expectations, perceived usefulness also contributes positively to intention to use (β = 0.188, $p = 0.002$). This supports H4 and indicates that recognizing tangible benefits from AI technologies increases users' willingness to adopt them. Beyond intention, perceived usefulness shows a direct positive relationship with AI use intensity (β = 0.289, $p < 0.001$), supporting H5. This suggests that when AI is seen as valuable for achieving work objectives, users are more likely to apply it purposefully and in a results-oriented manner, rather than using it superficially or sporadically. Regarding trust formation, the results indicate that perceived usefulness positively influences trust (β = 0.373, $p < 0.001$), supporting H6. This indicates that AI systems perceived as delivering reliable and beneficial outcomes in the workplace are more likely to be trusted, as consistent performance reinforces users' confidence in the technology.

H7 proposed that attitude toward use positively influences intention to use. The results strongly support this hypothesis (β = 0.540, $p < 0.001$), showing that when users hold favorable attitudes toward using AI in their work, they are significantly more willing to adopt and continue using these technologies in their daily professional activities. Moreover, intention to use is positively associated with AI use intensity (β = 0.375, $p < 0.001$), supporting H8. This finding indicates that users who express a stronger intention to use AI technologies are more likely to engage with them consistently and in ways aligned with accomplishing their work tasks.

Trust also plays an important role in shaping behavioral intentions. The results show that higher levels of trust are associated with stronger intentions to use AI (β = 0.194, $p < 0.001$), supporting H9. This indicates that when users trust AI technologies to perform reliably in work contexts, they are more likely to rely on them and integrate them into their professional routines. In addition to its indirect role via intention, trust has a direct positive effect on AI use intensity (β = 0.253, $p < 0.001$). This finding supports H10 and suggests that trust not only encourages adoption intentions but also facilitates deeper and more confident use of AI in work-related tasks, enabling users to depend on AI outputs when making decisions or completing assignments.

H11 proposed that organizational AI readiness positively influences perceived usefulness. The results provide strong support for this hypothesis (β = 0.630, $p < 0.001$), indicating that when organizations actively promote AI adoption and emphasize its strategic importance, employees are more likely to perceive AI as useful for accomplishing their work tasks. In addition, organizational AI readiness is found to positively influence psychological safety (β = 0.605, $p < 0.001$), supporting H12. This suggests that clear organizational signals and managerial encouragement regarding AI use can foster a climate in which employees feel safe to experiment, ask questions, and discuss challenges associated with AI implementation at work. Psychological safety, in turn, shows a strong positive effect on perceived ease of use (β = 0.460, $p < 0.001$), confirming H13. A supportive and non-threatening environment enables employees to feel safe seeking help and making mistakes. Therefore, in these cases, AI technologies are experienced as easier to use, as learning and adaptation become less stressful.

With respect to technostress, the results indicate a negative and statistically significant effect on attitude toward use (β = −0.151, $p = 0.004$), supporting H14. This finding highlights the detrimental impact of overload, complexity, and perceived loss of control on attitudinal evaluations of AI. It suggests that feelings of overload, complexity, or loss of control associated with AI use can undermine users' overall evaluations of AI in the work environment.

H15 tested the moderating effect of technostress on the relationship between psychological safety and perceived ease of use. The analysis revealed a negative and statistically significant moderation (β = −0.155, $p = 0.032$), supporting H15. This result indicates that while psychological safety generally enhances the perception that AI is easy to learn, understand, and control, this positive effect becomes noticeably weaker as technostress increases. In practical terms, the extent to which a psychologically safe environment encourages confident engagement with AI depends largely on the level of technological strain employees experience. A simple slope analysis (see Figure 3) illustrates this pattern. When technostress is low, psychological safety has its strongest positive influence on perceived ease of use, suggesting that in a calm, low-pressure context, a supportive and open climate makes it much easier for people to explore, experiment with, and feel comfortable using AI tools.

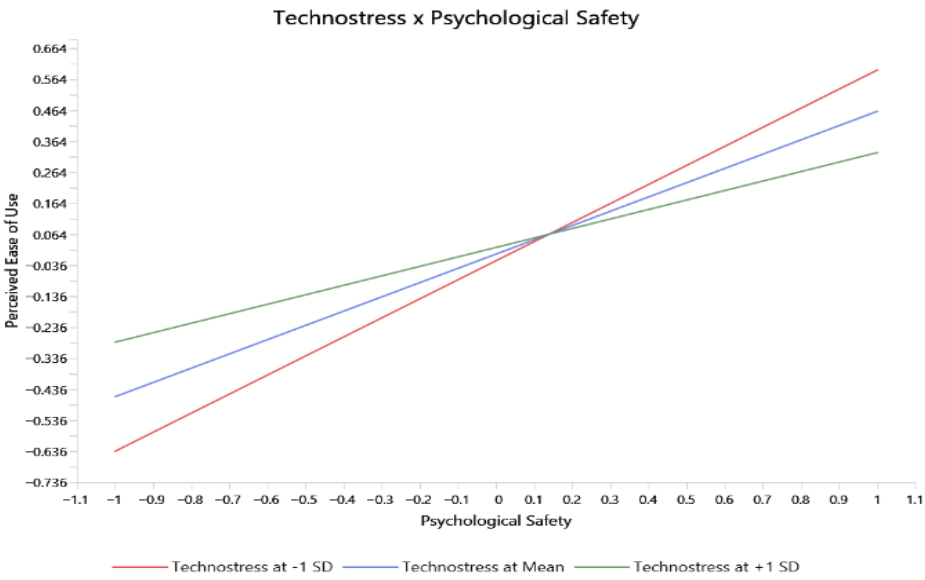

Figure 3. Simple slope analysis.

Substantively, the negative interaction (standardized β = −0.155) indicates a meaningful attenuation: as technostress increases, the positive effect of psychological safety on perceived ease of use becomes weaker. In practical terms, a psychologically safe climate still helps employees experiment with AI, but its benefits are partially diminished when overload, complexity, or constant connectivity are high. This suggests that psychological safety initiatives should be paired with technostress mitigation, such as workload and boundary management, training, and clear AI use norms.

At moderate levels of technostress, the relationship remains positive, but the effect is clearly reduced. At high levels of technostress, the slope flattens considerably: psychological safety still contributes positively, but its ability to promote favorable ease-of-use perceptions is substantially diminished. Importantly, this is an attenuating (rather than buffering or reversing) moderation, and technostress itself showed no significant direct effect on perceived ease of use, reinforcing that its primary role here is conditional. Overall, the findings suggest that even a genuinely supportive organizational climate cannot fully offset the challenges posed by high cognitive overload, anxiety about job displacement, or feelings of reduced control that often accompany intensive AI use. In essence, the analysis highlights an important boundary condition: the value of psychological safety in making AI feel approachable and manageable is real, but it is not unconditional; it weakens considerably when employees are already struggling with high technological pressure.

To better understand how the main antecedents influence both the intention to use AI technologies and AI use intensity in the workplace, we examined a series of mediation effects presented in Table 6. Indirect relationships were tested according to standard PLS-SEM practice, using a bootstrapping procedure with 5000 resamples. Every proposed mediation hypothesis was supported, with all indirect effects statistically significant and each mediation being partial. This indicates that while the mediating variables account for a meaningful portion of the relationship between the antecedents and the outcomes, the direct paths between them also remain significant. This pattern suggests that the ways employees form intentions and actually integrate AI into their daily work are multifaceted, involving both mediated mechanisms and independent direct influences.

Table 6. The mediating effects.

	Path Coefficient (β)	t-Value	*p*-Value	Mediation Type	Result
Technostress → Attitude → Intention to Use	−0.082	2.671	0.008	Partial	Confirmed
Perceived Ease of Use → Attitude → Intention to Use	0.112	3.486	0.000	Partial	Confirmed
Perceived Usefulness → Trust → Intention to Use	0.073	3.267	0.001	Partial	Confirmed
Attitude → Intention to → AI Use Intensity	0.203	5.017	0.000	Partial	Confirmed

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

To clarify the model's theoretical emphasis on AI use intensity, we interpret the mediation results in terms of primary and supporting mechanisms. The pivotal mediation is the Attitude → Intention → AI Use Intensity pathway, which shows how evaluations of AI are converted into sustained, task-integrated use. A second central mechanism is PU → Trust → Intention, which explains how perceived functional value fosters reliance under uncertainty, strengthening motivational readiness. The remaining indirect effects (e.g., technostress → attitude → intention) are complementary, specifying how organizational strain can erode these conversion processes.

H16 proposed that attitude mediates the relationship between technostress and intention to use.

The results indicate a negative and statistically significant indirect effect of technostress on intention to use through attitude ($\beta = -0.082$, $p = 0.008$), supporting H16. This finding shows that higher levels of technostress are associated with less favorable attitudes toward AI use, which in turn reduce employees' intention to use AI technologies at work. The mediation is partial, indicating that technostress primarily affects adoption intentions by undermining users' evaluative acceptance of AI rather than directly discouraging intention formation.

In line with the proposed model, attitude toward use serves as a central bridge connecting perceived ease of use to intention to use AI. The analysis revealed a clear, positive, and highly significant indirect effect of perceived ease of use on intention to use, mediated by attitude (β = 0.112, $p < 0.001$), providing strong support for H17. In summary, when employees find AI tools straightforward to learn, intuitive to use, and easy to manage in their daily tasks, this experience fosters a more positive overall perception of the technology. That favorable attitude, in turn, significantly increases their willingness to use AI and recommend it to colleagues. The mediation is partial, meaning that while attitude explains a substantial portion of the link, perceived ease of use still retains some direct influence on adoption intentions.

The results indicate that perceived usefulness influences intention to use partly through trust. Specifically, a positive and statistically significant indirect effect of perceived usefulness on intention to use via trust is observed (β = 0.073, $p = 0.001$), supporting H18. This finding suggests that recognizing the practical value of AI in work tasks alone is not sufficient to generate strong adoption intentions; rather, usefulness strengthens intention when accompanied by confidence in the technology's reliability and appropriateness. The mediation is partial, highlighting trust as an important psychological mechanism in this process.

H19 proposed that intention to use mediates the relationship between attitude and AI use intensity. The results confirm a positive and significant indirect effect of attitude on AI use intensity through intention to use (β = 0.203, $p < 0.001$), supporting H19. This finding indicates that favorable attitudes toward AI do not directly result in frequent or routine use. Instead, positive evaluations first strengthen employees' intention to use and advocate for AI, which subsequently leads to more consistent and integrated use of AI technologies in daily work activities. The mediation is partial, highlighting intention as a key mechanism through which evaluative judgments are translated into effective AI use.

5. Discussion

5.1. Theoretical Implications

The findings strengthen TAM- and HRM-oriented accounts of AI adoption by showing that intention alone is an incomplete endpoint: employees' favorable beliefs and intentions matter most when they are converted into sustained AI use intensity—frequent and routinized use in daily work. By modeling trust and technostress together, the study also advances a dual-mechanism view in which reliance under uncertainty (trust) and resource depletion (technostress) operate simultaneously, helping explain why organizations may observe enthusiastic intentions without commensurate value-creating AI use. Similar tensions have been documented among Generation Z in recruitment contexts, where ethical and human-centric priorities (e.g., transparency and fairness) amplify perceived benefits, while anxiety over AI tools intensifies the demand for human oversight and emotional reassurance [100].

This study examined Generation Z employees' acceptance and AI use intensity and tested an integrated model that combines core TAM beliefs with organizational AI readiness, psychological safety, trust, and technostress. Overall, the results support the idea that organizations benefit not only from AI adoption intensions, but from sustained AI use in day-to-day work [4,5].

Consistent with contemporary technology and AI acceptance research, perceived usefulness was the strongest driver of downstream outcomes, confirming that perceived performance value dominates evaluations of AI tools in work settings [1–3,29]. In contrast, perceived ease of use played a weaker role, suggesting that for digital natives, usability is often treated as a baseline expectation rather than a differentiator.

The results also highlight trust as a distinct pathway beyond instrumental beliefs. Trust directly increased both intention and AI use intensity, supporting arguments that AI adoption involves uncertainty and reliance decisions [10,11,16] and echoing recent evidence linking trust to continued use and reliance on AI tools [58,73].

Attitudinal and intentional mechanisms functioned as expected. Attitude remained an important affective summary of evaluations, and intention predicted AI use intensity, indicating that motivational readiness is necessary but not sufficient; employees still need to translate intentions into frequent and routinized AI use in daily work [4,28,30].

Beyond individual beliefs, organizational conditions also mattered. Organizational AI readiness increased perceived usefulness and was positively associated with psychological safety, suggesting that when AI adoption is encouraged and resourced, employees may interpret it as strategic support rather than coercion [7,8]. Psychological safety, in turn, improved perceived ease of use, consistent with evidence that safe learning climates facilitate experimentation and reduce the perceived effort required to master new digital tools [56,69].

Finally, technostress acted as a barrier. It reduced positive attitudes and weakened the beneficial effect of psychological safety on perceived ease of use, indicating that supportive climates can be undermined when digital strain is high. This is consistent with recent reviews and empirical studies showing that overload, complexity, and invasion can dampen acceptance and well-being in AI-enabled work [13,14,16,69].

5.2. Practical Implications

The results provide actionable HR and managerial guidance for organizations implementing AI with early-career employees. First, to promote effective—not just intended—AI use, leaders should combine performance framing (emphasizing usefulness) with trust-building practices, such as transparency about AI limitations, guidance on verification, and clear accountability norms. Second, psychological safety should be fostered through managerial behaviors that legitimize experimentation and learning from AI-related errors, which enhances perceptions of ease of use and supports adoption. Third, because technostress diminishes these benefits, organizations should actively manage digital strain through workload design, boundary protection, and targeted training that reduces complexity and uncertainty when using AI tools.

5.3. Limitations and Future Research

Several limitations should be noted. The cross-sectional design prevents strong causal inferences, and the sample is limited to Romanian Generation Z employees, which may restrict generalizability across cohorts and cultural contexts. AI use intensity was measured by two self-reported indicators: frequency and routine integration; future studies should include objective usage logs and task-level outcomes to capture the quality and goal-attainment aspects of AI-enabled work more directly. Further research could also employ longitudinal models to examine how trust and technostress co-evolve over time and to compare organizational interventions aimed at sustained AI use. Future research could extend the model by incorporating digital skills as an enabling capability that may strengthen the translation of intention into effective, task-integrated AI use, given evidence that digital skills can function as a meaningful moderator in intention-based models among young cohorts [101].

6. Conclusions

This research advances understanding of AI adoption by demonstrating how perceived usefulness and ease of use, shaped by organizational context, lead to trust, attitudes, intention, and ultimately AI use intensity among Generation Z workers in Romania. The results emphasize that performance value and reliance-related beliefs together explain why young employees intend to use AI and how they translate intention into frequent and routinized use in daily work.

From a theoretical point of view, this study contributes to technology acceptance theory by integrating three streams that are often treated separately: enacted use intensity as an outcome beyond intention, organizational climate as an antecedent of core acceptance beliefs, and stress- and uncertainty-related mechanisms that shape adoption. Specifically, the supported mediated and moderated relationships show that acceptance is both evaluative and contextual: perceptions of usefulness and ease of use matter, but their translation into intention and sustained AI use intensity depends on trust formation and on whether technostress allows organizational resources such as psychological safety to be converted into low-effort experiences.

From a practical perspective, for organizations seeking productive AI adoption, three priorities emerge. First, highlight and demonstrate concrete performance benefits, and align AI capabilities with task requirements to strengthen perceived usefulness. Second, invest in usability, onboarding, and responsive support to improve ease-of-use perceptions and foster trust, including transparent guidance on when and how AI outputs should be used. Third, cultivate psychological safety through supportive leadership and learning-oriented norms, while actively managing technostress through workload design, clear expectations, training, and boundary-setting practices that reduce overload and constant connectivity.

Overall, the manuscript's primary takeaway is that organizations realize value from workplace AI not by maximizing intention alone, but by enabling the conversion of intention into effective, task-integrated use through a dual pathway: building calibrated trust to support reliance under uncertainty and reducing technostress to protect employees' capacity to learn and integrate AI into daily workflows. This outcome-oriented perspective is the study's central contribution beyond previous TAM-based AI acceptance research.

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Institutional Review Board Statement: At the Bucharest University of Economic Studies there is no dedicated institutional review board or ethics committee for the ethical review and approval of non-interventional social science research, such as anonymous online questionnaire-based surveys involving perceptions, attitudes, or experiences of employees. This is consistent with the institutional structure and established practices at our university, where such low-risk, non-clinical studies do not fall under a formal mandatory ethics committee approval process. The study in question is a fully anonymous, voluntary, online survey with no collection of personally identifiable information, no sensitive personal data (as defined under the GDPR), no vulnerable populations, and no physical or psychological interventions. It therefore entails minimal risk to participants. In Romania, national legislation (including Law no. 206/2004 on the ethical conduct of scientific research, technological development, and innovation, as well as relevant provisions of the National Education Law no. 1/2011 and GDPR implementation rules) does not mandate formal ethics committee approval for anonymous, low-risk social science surveys of this nature. Researchers are nevertheless required,

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and we have strictly adhered, to uphold fundamental ethical principles, including respect for human rights, voluntary participation, informed consent, full anonymity, data protection in accordance with the EU General Data Protection Regulation (GDPR), and the right to withdraw at any time.

Informed Consent Statement: Informed consent was obtained from all participants at the start of the anonymous online questionnaire. Prior to providing consent, respondents were fully informed about the study objectives, the voluntary nature of participation, complete anonymity, data usage and protection in accordance with the EU General Data Protection Regulation (GDPR), the absence of risks, and their right to withdraw at any time. Acceptance of participation represented an implied consent.

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