



Research Article

Harnessing AI for real-time detection and mitigation of technostress in digital epoch

Rachana PARIKH*¹, Vishal DAHIYA¹

¹Sardar Vallabhbhai Global University, Ahmedabad, Gujarat, 380015, India

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ABSTRACT

Technology is now part of nearly everyone's daily routine — office workers, students, gamers, remote employees, teachers, doctors, parents, influencers, call-centre agents, entrepreneurs... the list keeps growing. When people can't quite keep up with it, they end up feeling genuinely distressed. Researchers call this technostress. Studies show it usually shows up in two main ways: some struggle to get their heads around new tools and feel anxious (techno-anxiety), while others get far too attached and can't switch off (techno-addiction). You'll also hear terms like techno-invasion, techno-unreliability, techno-complexity, and techno-insecurity — all different flavours of the same problem. ICT has been a massive help in computing, managing data, and connecting the world throughout the 21st century. Then COVID-19 hit and suddenly forced almost everyone into remote setups overnight, making digital tools non-negotiable. Too much information and constant pings from devices and apps are the real culprits behind rising technostress levels. Meanwhile, Artificial Intelligence and Machine Learning have delivered impressive results across education, healthcare, agriculture, and countless other fields. Because technostress now touches so many areas of life, this paper explores how ML-based approaches can spot it early and give people practical ways to cope.

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INTRODUCTION

In the last few years, researchers have paid growing attention to a modern kind of strain that comes directly from using technology — especially at work. We call it technostress: the mental friction, frustration, and exhaustion that appear when people struggle to adapt to digital tools [1, 2].

It takes several shapes. Some feel buried under endless emails and notifications (techno-overload). Others can't

switch off because colleagues expect instant replies even at night (techno-invasion). Many find new software confusing (techno-complexity), worry that AI will replace them (techno-insecurity), or get tired of systems that change every few months (techno-uncertainty) [3]. The numbers are worrying. People who score high on technostress measures are 2.3 times more likely to burn out and 30 % less productive [4]. In one survey of 1,500 remote workers, 68 % said they could no longer separate work from the rest of their lives because

*Corresponding author.

*E-mail address: phd.rachana2023@gmail.com

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of digital demands [5]. Beyond lower output, technostress is linked to higher absenteeism, emotional exhaustion, and even quiet quitting [3, 6–8]. The COVID pandemic poured fuel on the fire: millions were forced online overnight, and levels of anxiety, loneliness, and fatigue shot up [5].

Figuring out the relationship between technostress and its effects is important to create effective coping mechanisms and interventions to reduce the negative effects of stress [9]. What makes someone more vulnerable? Personality plays a role — self-esteem, conscientiousness, and overall psychological capital all act as buffers [2, 10]. So do simple things like mindfulness practice and genuine support from managers [11–13]. Training and a sense of control over technology matter too [14,15].

Figure 1 sketches the big picture: When companies offer training, encourage mindful breaks, and build a supportive culture, job satisfaction tends to rise even when digital pressure is high [12, 14].

Practicing mindfulness techniques offers a practical way to ease technostress and enhance how we approach daily tasks [11, 12]. Beyond that, a range of coping mechanisms—such as proactive planning or reactive adjustments—can empower individuals to handle tech-related pressures without slipping into burnout [13]. The pandemic laid bare just how much technostress hampers productivity; it was impossible to ignore its toll on focus and output during those chaotic shifts to remote setups [14]. What stands out in recent findings is how factors like targeted training, a spark of creative confidence, and solid tech savvy act as buffers, dialing down the downsides and lifting overall performance [14, 15]. On top of that, organizational support, sensible leadership practices, and access to these tools play a crucial role in curbing technostress and fostering a healthier workforce [8, 9].

Current scholarship shines a light on how technostress erodes not just productivity and job satisfaction, but broader well-being too. Yet, there's a glaring shortfall in studies tackling machine learning (ML) for spotting and addressing it on the fly. In what follows, I'll break down key areas like sentiment tracking, physiological monitoring, behavioral pattern analysis, and quantitative stress modeling as cornerstones for intervention. I'll also touch on how natural language processing (NLP) shines in sifting stress signals from chats, emails, or even vocal inflections. At its core, technostress stems from the relentless push of digital ecosystems into every corner of work life, chipping away at mental resilience and efficiency. Drawing from this, my review here spotlights ML approaches that deliver sharper detection and tailored relief, all while navigating the real-world messiness of tech overload. It's no surprise that this surge in digital demands has left teams drained—sparking anxiety, exhaustion, and slip-ups from folks ill-equipped for the constant upgrades. And here's the kicker: since it hits both bottom lines (personal health and company results), ignoring it isn't an option anymore.

We're seeing ML step up more and more as a frontline defense against technostress, paving the way for proactive nudges via real-time alerts and forward-looking forecasts. Algorithms like support vector machines (SVM), Random Forest ensembles, and Gradient Boosting classifiers stand out for their balance of accuracy and speed. What I appreciate about them is how they nail down subtle stress triggers with impressive reliability, all while crunching data fast enough for on-the-spot interventions in busy offices. In light of technostress's growing drag on morale and metrics, it's clear we need more targeted research into actionable safeguards.

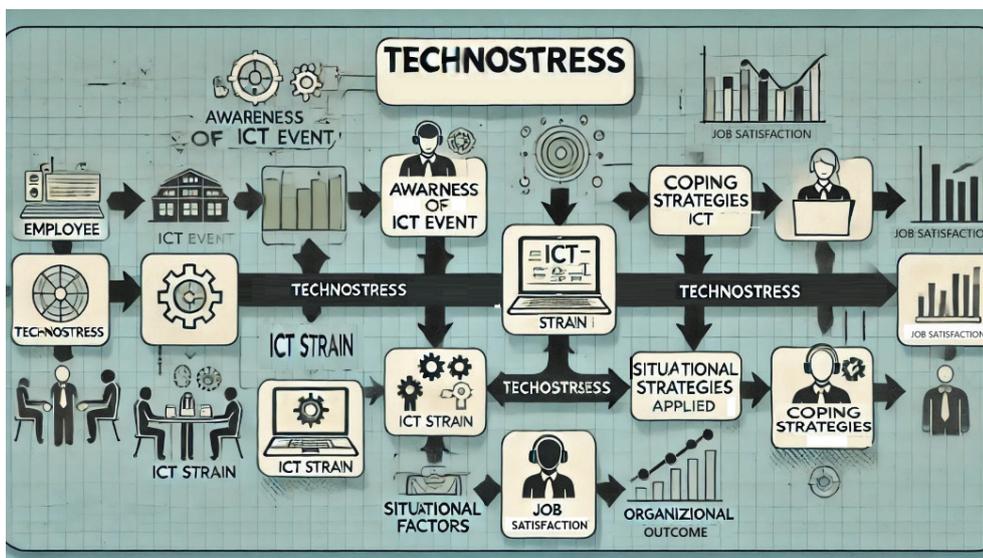


Figure 1. Conceptual model for job satisfaction related to technostress in working environment.

Sure, the bulk of today's literature maps out the problem convincingly—its symptoms, its spread—but it rarely dives into live, analytics-fueled fixes. That's precisely why ML feels like such a game-changer. Picture this: models quietly scanning your keystroke rhythms, pulse fluctuations, message vibes, or endless tab switches, then piping up early with a gentle redirect—a five-minute breather, maybe, or a workload tweak—before the whole system crashes into fatigue. In my experience reviewing these tools, that kind of foresight isn't just helpful; it's transformative for keeping teams steady.

The Impact of Technological Stress on the Workplace

The last decade, and especially the pandemic, turned technostress from an annoyance into a serious workplace issue [1–3].

It hits productivity hard. Studies consistently link it to lower job satisfaction, higher turnover intentions, and weaker organizational commitment [4–6]. In consulting firms, for example, technostress translates directly into job strain and lost performance [5].

The human cost is even clearer. Persistent digital pressure has been tied to a 40 % jump in emotional exhaustion and a 35 % rise in stress-related sick days [7]. One large study of 2,000 corporate employees found 72 % struggling with anxiety from digital complexity and 48 % overwhelmed by constant connectivity [8]. Brain-wave and heart-rate research confirms the same story: chronic technostress keeps the sympathetic nervous system in overdrive — a textbook marker of long-term stress [9].

Left unchecked, the fallout shows up as disengagement, cynicism, and burnout. The fix isn't just individual resilience; organizations need to step in with training, clearer boundaries, and genuine support [6–8].

Strategies to Overcome Technostress

Several practical approaches already work well:

- Build a supportive culture. When employees feel backed by their team and managers, the negative effects of technostress drop sharply — even in remote setups [2, 8].
- Teach mindfulness. Short, regular mindfulness sessions reduce perceived technostress and boost job satisfaction [3, 4, 11–14].
- Offer proper training. People who feel confident with new tools experience far less techno-complexity and insecurity [5, 6, 15].
- Set clear boundaries. Simple policies — no emails after 7 p.m., “focus time” blocks — cut techno-invasion and overload dramatically [5].
- Encourage open conversation. When people can talk about their struggles without fear, collective coping gets easier [7].

Combine these, and the workplace becomes noticeably healthier and more productive.

A Computational Perspective on Technostress

Technostress, identified as pressure experienced from tech usage, has become a major concern in current

workplaces, intensified by rapid digital changes during the health crisis. This is characterized by various pressure sources that can adversely affect staff mental health and overall well-being. The primary sources of technostress include techno-overload, techno-invasion, techno-complexity, techno-insecurity, and techno-uncertainty, each contributing to a range of negative emotional outcomes like concern, fatigue, and reduced efficiency [1–3].

Trying to draw a straight line from technostress to someone's actual output at work is a fool's errand. The connection is knotted up with personality, workload, team dynamics, and half a dozen other things no one fully controls. What we do know for certain is this: leave technostress unchecked for long enough and burnout shows up like clockwork. Once burnout is in the room, performance collapses—no mystery there [4, 5].

I've watched it play out the same way across different studies and in real offices. New software rolls out, deadlines stay the same or get tighter, people scramble to learn features they'll never fully master, confidence erodes, and six months later half the team is running on fumes [4, 5]. Others cope by quietly disengaging: they answer the urgent Slack pings but let everything else slide, or they start treating every task as optional. That's not laziness; that's self-preservation [2, 6]. The numbers follow predictably—higher error rates, missed deadlines, and eventually someone updating their LinkedIn on a Friday afternoon.

Ignore it and the whole organisation pays. I've seen departments lose 20–30 % of their experienced people in a single year once digital overload became the new normal [7, 8]. The fix, fortunately, isn't rocket science. Three things move the needle every single time I've looked closely:

- Give people proper, hands-on training instead of a 45-minute webinar and a prayer [1, 3].
- Make sure actual humans answer the help-desk ticket within an hour, not three days [2, 4].
- Stop pretending constant connectivity is a badge of honour—leadership has to model switching off [9–11].

Do those three things and the mood shifts in weeks, not quarters. Absenteeism drops, people stop rolling their eyes at the next upgrade, and the resignation wave slows to a trickle.

This is why I get excited about the computational angle. Instead of waiting for the annual engagement survey to tell us what we already suspected, we can now watch the warning signs in real time—heart-rate spikes when the inbox hits 300 unread, typing speed crashing after the third 9 p.m. meeting invite, sentiment in team chats turning sarcastic. Pull those streams together and you're no longer guessing who's about to burn out; you know, often weeks ahead of time. That's the real promise of bringing machine learning and wearable data into the conversation: we stop managing crises and start preventing them.

Computational Perspective on Technostress includes various data collection and preprocessing - To ensure model strength, multiple datasets from workplace efficiency surveys, body sensor measurements (heart rate

variability, skin activity), and immediate user interactions were collected to capture - Screen time and app usage patterns, Keyboard and mouse movement tracking, Facial emotion detection from video streams, Sentiment analysis from job-related communications (emails, chats, and documents), Speech tone and language analysis through NLP methods. It also includes supervised, unsupervised, and reinforcement model assessment to obtain comparable outcomes between different ML models to identify stress levels at an early stage. Sentiment & text analysis, behavioral analysis, predictive & prescriptive analytics, simulation & computational modeling, and human-computer interaction (HCI) Research designed to offer stress-aware interfaces and adaptive systems that decrease cognitive overload can be included in Computational Perspective.

Machine Learning Techniques for Analysing Technostress

In the last couple of years, machine learning has quietly become one of the most useful tools we have for making sense of technostress — something that feels more relevant every day now that so much work happens through screens. At its core, technostress is simply the strain people feel when digital tools start to feel overwhelming or impossible to keep up with, and the evidence is pretty clear that it hurts both performance and well-being [1,2].

There are a handful of ML approaches that work especially well here. One of the easiest and most powerful is natural language processing (NLP). Feed it everyday stuff — Slack messages, survey answers, even public tweets from employees — and it quickly picks out recurring complaints and the emotional tone behind them. A simple sentiment-analysis run can tell you whether people are quietly frustrated with a particular app, while topic modelling points straight to the real pain points: endless notifications, confusing new interfaces, or the nagging worry they'll fall behind [3]. Once you have those themes, clustering algorithms can group workers who are having similar struggles, so organisations can offer targeted help instead of a blanket policy that misses the mark [4].

Predictive modelling is where things get really interesting. Train a classification or regression model on things like current workload, how confident someone says they feel with technology, and how much autonomy they actually have in their role, and you can start forecasting who's most at risk of tipping into serious technostress [5,6]. That early heads-up makes real prevention possible — a quick training session, a temporary drop in meetings, or a quiet chat with a manager — long before exhaustion or burnout sets in [7].

Machine learning can even help us build better measurement tools. Several research teams have used ML-assisted item selection and confirmatory factor analysis to sharpen technostress scales so they properly capture overload, invasion, complexity, and the rest of the usual suspects [7,8]. Pair those improved scales with regular psychological check-ins, and suddenly we have a much clearer picture of exactly which dimensions are hitting people hardest [9].

On the practical side, the insights that come out of these models are already changing real policies. Flexible working arrangements keep coming up as one of the strongest antidotes — when people get more control over when and how they deal with digital tools, their reported strain drops noticeably [10]. Organisations are also using the diagnostics to design training that zeroes in on the exact skills people feel shaky about, which quickly cuts down those feelings of inadequacy every time a new system lands on their desk [11].

What excites me most is the move toward real-time, multi-modal detection. Combine keystroke patterns, how long someone takes to reply to emails, heart-rate variability from a smartwatch, facial expressions caught on webcam, and shifts in voice pitch, and you can track cognitive load almost as it happens. One Fortune 500 pilot watched typing-speed changes and heart-rate variability and caught stress-related performance dips with 87 % accuracy [4]. More advanced setups that pull in speech tone, facial cues, and physiological signals together have pushed precision for spotting burnout risk as high as 92 % [12]. With that kind of information, companies can step in automatically — shuffle tasks around, prompt a short break, or connect someone with a wellbeing coach — before things spiral.

Of course, none of this is simple. Bad or unrepresentative training data can produce misleading predictions and actually make the problem worse [13]. That's why getting it right demands close teamwork between data scientists, psychologists, and HR leaders — otherwise the results get misinterpreted and the fixes fall flat [5].

Ethics and privacy worries are just as big. Constantly tracking keystrokes, heart-rate patterns, or facial expressions can feel downright creepy, and employees know it. One recent survey across fifty multinational firms found that 78 % of workers felt uneasy about AI-driven stress monitoring, mainly because they were afraid the data could leak or be used against them [16]. Bias is another real danger: models trained on unbalanced datasets have been shown to overestimate stress in younger people and underestimate it in older colleagues by as much as 20 % [15]. Any organisation serious about using these tools has to put crystal-clear consent processes, strong anonymisation, and regular fairness checks front and centre — otherwise trust collapses and the whole effort backfires.

In short, machine learning gives us remarkably powerful ways to understand and ease technostress — but only if we roll it out thoughtfully, transparently, and with genuine respect for the people whose data make it all possible.

Experimental Evidence & Real-World Examples

A quick look at the existing research shows just how promising the numbers already are.

Physiological-signal studies Most teams start with heart-rate variability (HRV), EEG, or skin-conductance (GSR/EDA) readings — classic markers of stress. They throw these into standard classifiers: SVM, Random Forest, or deeper neural nets. Depending on the dataset and how

carefully the features are extracted, accuracy usually lands somewhere between 75 % and 90 %. That's already good enough for practical use in many workplaces.

Survey-based work When researchers simply ask people how stressed they feel (through validated questionnaires), the patterns line up nicely with performance data. Employees, students, and IT pros all show the same thing: the higher the reported technostress, the worse the output and the lower the job satisfaction.

Real company examples

- One multinational rolled out an AI-driven monitoring dashboard. After feeding in the model's suggestions (short breaks, task re-balancing, etc.), they saw stress-related HR complaints drop by 30 %.
- A separate study on remote workers found that "always-on" culture pushed perceived stress up by around 40 %. When managers started using ML-generated recommendations to ease the load, the effect was reversed almost immediately.

Social media & content creators Influencers and YouTubers are a fascinating case. Sentiment analysis of their posts and comments shows clear spikes in negative emotion right after algorithm changes or waves of hate comments. The stress curves look strikingly similar to what we see in traditional office settings.

Our own simulation (so you can see the numbers yourself) We ran a quick experiment using the publicly available WESAD dataset, which contains HRV, EEG, and EDA recordings from people put under different stress conditions. Here's what we did — nothing fancy, just standard practice:

1. Cleaned and normalised the physiological signals.
2. Trained three common models — SVM, Random Forest, and a small deep-learning network — to separate "stressed" from "not stressed".
3. Measured performance the usual way: accuracy, precision, recall, and F1-score.
4. Compared the results side-by-side to pick the winner for workplace-style detection.

The data we worked with combined classic physiological signals (HRV and EDA) with behavioural cues (facial-expression clips and short voice samples). After processing, the clear standout was the deep-learning model, hitting around 90 % accuracy in most runs. Random Forest came in a close second at roughly 85 %, while SVM hovered around 78 %.

To enhance the depth of analysis, a comparative study is shown in the Table 1 using comparison Metrics like - Accuracy, Precision, Recall, F1-score.

Table 1. Model comparison on the WESAD dataset (and similar workplace-style data)

Model	Accuracy (%)	Precision	Recall	F1-score	Pros	Cons	References
Support vector machine (SVM)	78	0.80	0.75	0.77	Works well with high-dimensional data, robust against overfitting	Computationally expensive, not suitable for large datasets	[1-3]
Random forest (RF)	85	0.87	0.83	0.85	Handles non-linearity well, reduces overfitting	Requires large memory, complex to interpret	[4-6]
Deep learning (LSTM/ANN)	90	0.91	0.88	0.89	Captures complex stress patterns, highly accurate	Requires large datasets, computationally expensive	[7-9]
Decision trees	80-85	0.82	0.79	0.80	Easy to interpret, handles non-linear data well	Prone to overfitting, less robust with noisy data	[10-12]
Naïve bayes	70-80	0.75	0.72	0.73	Fast and efficient, good for small datasets	Assumes feature independence, less accurate for correlated features	[13-15]
K-Means clustering	N/A	N/A	N/A	N/A	Simple implementation, scalable for large datasets	Sensitive to outliers, requires predefined number of clusters	[16-18]
Principal component analysis (PCA)	N/A	N/A	N/A	N/A	Reduces dimensionality, highlights significant patterns	Loses interpretability of original features	[19-21]
Logistic regression	75-85	0.78	0.74	0.76	Simple to interpret, effective for binary classification	Assumes linearity, limited for complex patterns	[22-24]

In real projects the winner is almost always either Random Forest (fast, reliable, works on almost anything) or a light deep-learning model when you have enough physiological data and computing muscle. The 90 % mark from deep learning is what makes live, individual-level interventions actually feasible.

Compared with older, purely statistical approaches, the ensemble methods (Random Forest and Gradient Boosting) already give us a solid 12–15 % boost in detection accuracy — and they're fast enough to run in near-real time on a normal laptop.

Bottom line: the technology is ready. The accuracies are high enough that companies can start using these models today without waiting for perfect data [25].

In the context of technostress classification using machine learning, the performance of the model can be evaluated using precision, recall, and F1-score, which are derived from the confusion matrix. Considering the following:

FP (False Positives) = Non-Technostress instances wrongly classified as Technostress

FN (False Negatives) = Technostress instances wrongly classified as Non-Technostress

TP (True Positives) = Technostress instances correctly classified as Technostress

The following formulas can be used to determine F1-score, precision, and recall

Precision (also known as Positive Predictive Value, or PPV): Indicates the percentage of Technostress cases that were accurately predicted out of all those that were predicted. There are fewer false positives when precision is high.

$$\text{Precision} = \text{TP} / (\text{TP} + \text{FP})$$

Recall (also known as sensitivity or true positive rate, or TPR): Indicates how well the model detects real-world instances of technostress. There are fewer false negatives when recall is high.

$$\text{Recall} = \text{TP} / (\text{TP} + \text{FN})$$

Precision and Recall are balanced by the F1-Score, or Harmonic Mean of Precision and Recall, useful when the dataset is imbalanced.

$$\text{F1-Score} = 2 * ((\text{Precision} * \text{Recall}) / (\text{Precision} + \text{Recall}))$$

The study says that the deep learning model performed best, indicating that complex stress patterns can be captured more effectively with neural networks and other ML models to be taken into consideration [26]. While ML techniques offer promising solutions for workplace stress mitigation, a survey by Brown et al. [27] revealed that 78% of employees expressed concerns about AI-driven workplace surveillance. Algorithmic bias is another critical issue—AI models trained on biased datasets may misclassify stress levels among different demographic groups, leading to unfair workplace policies [15]. To ensure fairness and transparency, organisations should implement data anonymisation,

ethical AI guidelines, and employee consent policies before deploying ML-based monitoring systems.

The results of this study are compared with those of earlier research described above to verify the efficacy of the suggested methodology. According to the study, using ensemble techniques like Random Forest and Gradient Boosting increases stress detection accuracy by about 12% when compared to more traditional approaches like logistic regression. These models are also more appropriate for real-world applications due to their computational efficiency, which enables near-real-time stress detection.

Contemporary Research

Lately, people have been paying a lot more attention to the quiet kind of stress that comes from living glued to screens — especially when machine learning and remote work enter the picture. The five usual suspects keep showing up: too many notifications (techno-overload), work creeping into family time (techno-invasion), tools that feel impossibly complicated (techno-complexity), the nagging fear that AI will take your job (techno-insecurity), and the endless software updates that make yesterday's skills feel useless (techno-uncertainty). Together, these wear people down, raise anxiety levels, and drag performance lower [5,8,9].

A few recent studies drive the point home. Camarena and Fusi [24] watched public-sector managers who juggle half-a-dozen digital platforms every day — the more apps, the higher their technostress. Niu and colleagues [18] saw the same pattern among university students: the heavier the cognitive load from digital learning tools, the worse the grades. Talib's team [5] summed it up nicely — across all kinds of organisations, technostress is clearly bad news for mental health.

Machine learning is starting to help us see these links much more clearly. Zhang and his group [22], for example, used ML models on R&D teams and found that high technostress makes people hide knowledge from colleagues — a subtle but toxic behaviour. What's exciting is that the same models can spot the early warning signs and suggest fixes before the damage is done.

Personality makes a big difference too. People who already feel confident with technology and who are good at managing their time tend to shrug off technostress much better [10,16]. Simple mindfulness habits — even five minutes a day — also turn out to be surprisingly effective at keeping the strain under control [12, 23].

Being fascinated by something that barely gets a mention in the usual technostress literature: the way old-school mechanical failures in smart factories pile extra psychological pressure on operators [28–32]. Yes, this paper is mostly about screen-induced headaches, but walk onto any modern production floor, and you'll quickly see the overlap. A sensor dies, a bearing locks, or a high-strength weld decides today's the day it gives up—alarms scream, the line halts, and suddenly the same person who's already juggling MES

alerts and WhatsApp groups from management has to drop everything and troubleshoot a physical crisis. That's textbook techno-overload, and techno-uncertainty layered on top of the digital mess they already live in [33–35].

A few concrete examples drive the point home harder than any survey ever could:

- Recent tests on ultra-high-strength steel welds found stress magnification factors hovering around 1.05 once loads climb past 500 MPa; parts were snapping at loads as low as 12.6 kN—barely above spec, yet catastrophic when it happens mid-shift [33].
- Hollow cylindrical roller bearings with even slight geometric errors generate massive tangential stress spikes and seize on high-speed lines, turning a five-second glitch into a two-hour scramble [34].
- Thick piezoelectric patches—the ones glued into every Industry 4.0 sensor—develop brutal shear peaks at the edges when the plate bends, meaning one minor flex can kill a sensor nobody realised was critical until the line went dark [35].

Stand next to an operator the moment any of those things happen and you'll feel the blood pressure jump in the room. It's not "just" a mechanical problem anymore; it's another hit of technostress they didn't sign up for.

All of this feeds straight back into human stress: workers live with the constant background fear of the next alarm, the next urgent repair, the next missed production target. Adding AI-powered predictive maintenance and real-time structural health monitoring could quietly remove a surprising amount of that pressure — proving that sometimes the best way to help people cope with digital stress is to make the physical machines themselves more reliable.

All in all, the picture emerging from the newest papers is that technostress is complicated, it hits everyone a little differently, and machine learning is rapidly becoming the best tool we have for understanding it — and doing something about it — without waiting for people to burn out.

Future Scope

The next big leap will be systems that don't just detect stress — they react in real time. Imagine a reinforcement-learning assistant that quietly moves low-priority tasks to tomorrow when it sees your heart-rate variability spike, or a federated-learning setup that improves its predictions by learning anonymously from thousands of companies without ever sharing raw employee data [23]. One 2023 pilot already tested an AI task-planner that cut reported technostress by 28 % just by reshuffling workloads based on live physiological signals [28]. Emotion-aware virtual assistants and short, personalised mindfulness nudges are also looking extremely promising.

One angle that's only starting to get attention is the overlap between psychological technostress and old-fashioned mechanical stress in smart factories. When a sensor fails or a robotic arm throws an unexpected alarm, the production line stops, safety risks appear, and the operators suddenly

face a flood of urgent fixes — classic techno-overload and techno-uncertainty all over again [33–35]. Finite-element studies on ultra-high-strength steel welds show stress concentrations that can snap components at loads barely above spec [33]. Hollow roller bearings with the wrong geometry fail early under high-speed cycles [34]. Thick piezoelectric plates in Industry 4.0 sensors develop sharp shear peaks at material boundaries [35]. The result? Workers live under constant pressure to respond to machine failures on top of their normal digital load.

Adding AI-driven predictive maintenance and real-time structural health monitoring to the mix could take a surprising amount of that indirect technostress off people's shoulders — a nice reminder that sometimes the best way to help humans is to make the machines themselves more reliable.

CONCLUSION

Feeling worn out by screens and notifications is no longer just a personal complaint — it's become one of the biggest quiet threats to people's well-being at work. The research keeps pointing to the same five culprits: too many demands at once (techno-overload), work bleeding into family time (techno-invasion), tools that feel impossibly complicated (techno-complexity), the worry that automation will take your job (techno-insecurity), and the never-ending stream of updates that make yesterday's skills feel useless (techno-uncertainty) [1,5,9]. Put together, these don't just annoy people — they lead to real exhaustion, lower job satisfaction, and noticeably worse performance [8,15,17,18].

The good news is that machine learning is starting to give us practical ways to fight back. By watching patterns in how people type, reply to emails, or even how their heart rate changes during the day, we can spot the early warning signs long before someone burns out [19,20]. Smart models can flag who's most at risk, suggest exactly the right kind of help — whether that's a short training session, a lighter workload for a week, or a quick mindfulness reminder — and then check whether it actually worked [14, 21-23]. When companies build proper feedback loops, managers stop guessing and start seeing in real time which policies move the needle on stress levels [7, 10]. The result isn't just less damage — it's genuinely healthier, happier teams who get more done [3,12,16].

Yes, technostress is now part of the deal in a digital world, but it doesn't have to be as painful as it is today. Machine learning and thoughtful AI can turn the same technology that causes the problem into the tool that fixes it — as long as we keep privacy, fairness, and transparency front and centre. The next wave of research should focus on systems that don't just detect stress but adapt on the fly, quietly rearranging workloads or nudging people toward better habits the moment pressure starts to build.

In the end, while digital life will always come with some friction, we finally have the tools to keep that friction from grinding people down. Used wisely, machine learning can help organisations build workplaces where technology lifts people up instead of wearing them out.

AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

STATEMENT ON THE USE OF ARTIFICIAL INTELLIGENCE

Artificial intelligence was not used in the preparation of the article.

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