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Emotional intelligence and disruptive technologies. a human-computer interaction overview on human perception of AI

Inteligencia emocional y tecnologías disruptivas: una perspectiva desde la interacción persona-ordenador sobre la percepción humana de la IA.

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Resumen

El avance tecnológico y el auge de la inteligencia artificial han abierto un interesante debate en la relación entre humanos y computadoras. Sin embargo, la curva tecnológica actual impone una realidad donde la adaptación humana se ve superada por la integración algorítmica. Este artículo examina la rápida adopción corporativa de la inteligencia artificial y el consiguiente rechazo estructural no solo del trabajador humano, sino también de la percepción social de las tecnologías en su conjunto. Analiza los marcos teóricos de la automatización basada en tareas, la inflación de la infraestructura tecnológica y los vectores de desplazamiento socioeconómico que se extienden desde las economías desarrolladas hacia centros tecnológicos emergentes como la ciudad de Ho Chi Minh, Vietnam. Este artículo describe el panorama en una de las economías de más rápido crecimiento del sudeste asiático, Vietnam, y también a nivel global, demostrando que la mercantilización de la percepción humana elimina la prima económica que antes se otorgaba al trabajo humano y que los rasgos emocionales son clave para la recepción de tecnologías disruptivas.

Palabras clave: Inteligencia emocional, computación afectiva, interacción humano-computadora, capitalismo cognitivo, bienestar subjetivo, automatización basada en tareas, PLS-SEM.

Abstract

Technological advancement and the rise of artificial intelligence have allowed an interesting space to be discussed within the climate of humans and computers. Yet, the current technological curvature dictates a reality where human adaptation is fundamentally outpaced by algorithmic integration. This paper examines the rapid corporate adoption of artificial intelligence and the resulting structural rejection not only of the human worker but also of the social perception of technologies as a whole. This paper analyses the theoretical frameworks of task-based automation, the inflation of technological infrastructure, and the socioeconomic displacement vectors extending from developed economies to emerging technological hubs like Ho Chi Minh City, Vietnam. Ultimately, this paper establishes the landscape across one of the most rapidly developing economies in South-East Asia, Vietnam, and globally as well, showing that the commodification of human perception removes the economic premium previously afforded to human labour and that emotional traits are key to the reception of disruptive technologies.

Keywords: Emotional intelligence, Affective computing, Human-computer interaction, Cognitive capitalism, Subjective well-being, Task-based automation, PLS-SEM.

INTRODUCTION

Globally, artificial intelligence (AI) is now more of a reality: the harsh, present-day framework of the enterprise and the educational environments around the world (Acemoglu & Restrepo, 2019). Technological evolution is accelerating, as Large Language Models (LLMs) are rising to remarkable heights faster than ever before (Brynjolfsson et al., 2025; Dehouche, 2025). However, the adoption of personal computers and the internet is facing a struggle of such “aggressive integration", meaning that it opens up massive corporate possibilities for optimising organisational performance, predictive analysis and automation of content at scale (Dehouche, 2025; Noy & Zhang, 2023). This is now shown as a far less cheery path for the future; as Eloundou et al., (2023), Flores (2026), and Hui, (2024) state, it is one of structural rejection of the 'human worker vs machine'. This paper seeks to bridge the gap between the two views and analyse the emotional aspect of the intrinsic nature of the human being and its reflection on technology.

This AI technology that was first welcomed has created a society of mistrust, in part because the decisions AI companies are making within these disruptive systems are becoming increasingly difficult to regulate and understand (Chaudhary, 2024; Marey et al., 2024). Thus, this obfuscation of understanding regulation and modelling is not only an engineering problem for the enterprises that massively train AI models, such as Anthropic and OpenAI, but a governance one with significant ethical dimensions for people whose livelihoods and education are judged by algorithms (Preston, 2024; Cinar, 2026; Fuchs, 2024).

In order to understand these discrepancies, this paper adopts a theoretical and empirical understanding of AI-induced displacement, from a framework which draws on the concepts of labour economics and developmental psychology to form a Human-Computer Interaction (HCI) analysis. For instance, if a company or school can program a human thought's rhythmic and statistical properties into a well-designed set of prompts, the incentive for human beings to continue performing these 'routine' mental computations becomes lost (Noy & Zhang, 2023; Eloundou et al., 2023; Brynjolfsson et al., 2025). AI writing assistants, among other applications, have been shown over and over again to be adopted in a way that is unprecedented in any field of professional life (Dehouche, 2025; Flores & Luna, 2024), and that consequently has affected the economy and available data, most traditional models of education and cognitive development. However, the place of human emotion has been marginalised or even made an obstacle to the cognitive process Pekrun, 2024; Yuvaraj et al., 2025).

Furthermore, this paper examines the role of linguistic and emotional expertise in enabling enterprise AI to be adopted, leading to systemic job replacement and changes to human roles. The overall result is an indication of the integration of generative AI as a way to commodify human intellect - dubbed the "digital harvesting of affective and cognitive micro-labour" (Flores, 2023; Flores, 2025a). This paper aims to establish that Emotional Intelligence (EI) is still the most important non-automated competency, important as a mediator of Subjective Well-Being (SWB) and that HCI systems should evolve to embrace, extend and preserve the competency.

This work has three contributions. First, it offers a theoretically integrated framework that covers cognitive capitalism, affective computing and positive psychology (Fuchs, 2024; Cinar, 2026). Second, it offers empirical PLS-SEM evidence in an emerging technological context based on previous research (Bilandzic, 2023; Flores, 2026; Flores & Luna, 2024). Third, it introduces design principles for emotionally intelligent AI architectures which can be used as augmentative instead of extractive forces in education and enterprise (Flores, 2023; Flores, 2025b; Luna et al., 2026; Ocaña et al., 2021).

Theoretical Framework

This paper presents the paradigm shifts in traditional economics that dictate that technological automation is central to the present context of structural rejection of the human worker (Acemoglu & Restrepo, 2019). Traditionally, the neoclassical economic models dealt with technological change as a general factor-augmenting phenomenon that was naturally considered to increase the productivity of both labour and capital (Acemoglu & Restrepo, 2019). The prevailing view was that some jobs were likely to be lost but that this would result in employment being lost overall and jobs would be created elsewhere to compensate (Acemoglu & Restrepo, 2019). A more disaggregated, task-based approach has greatly compromised this orthodox vision, as it views production in terms of the specific cognitive and physical tasks allocated to a person or machine (Acemoglu & Restrepo, 2019; Eloundou et al., 2023).

Generative AI is not like the other waves of automation; it is disrupting the historical balance (Brynjolfsson et al., 2025; Eloundou et al., 2023; Siddiqui et al., 2026). Whereas automation previously took the place of routine physical work, cognitive automation has started to directly replace non-routine, knowledge-based work – legal reasoning, financial analysis, scientific writing and code generation – thus reducing the scope of work where humans have a comparative advantage (Brynjolfsson et al., 2025; Eloundou et al., 2023; Siddiqui et al., 2026). This transformation needs paradigm changes in cognitive and psychological profiles, as the AI system(s) will learn from large amounts of human interaction and activity in the digital realm, and eventually emulate and replicate cognition (Flores & Luna, 2024). The consequences for jobs are serious as described: GPT-4-like models could affect a significant portion of the tasks performed by most knowledge-intensive workgroups in the US economy (Eloundou et al., 2023), and some studies suggest that the models would chiefly disrupt mid-skill knowledge jobs outside the US economy (Siddiqui et al., 2026; Hui et al., 2024).

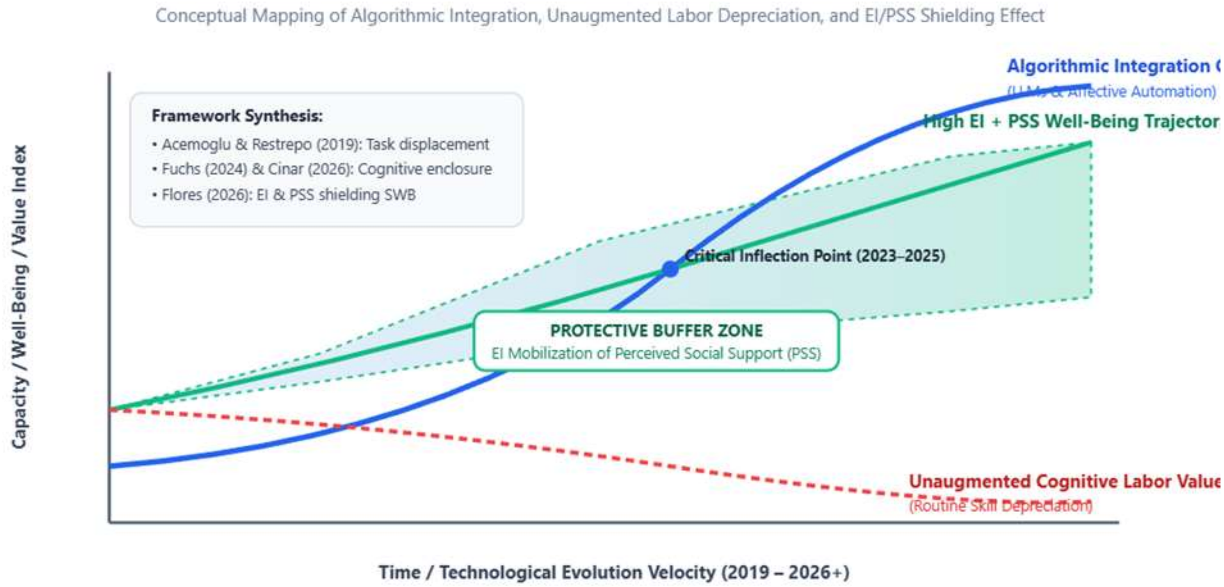
However, it is not just a problem of task substitution. It is the human-generated training data that constitutes the ultimate commodification of human perception within algorithmic platforms, which are able to take unpaid affective and cognitive labour from posts, reviews, conversational records, academic writing and related activities (Bilandzic, 2023; Preston, 2024; Fuchs, 2024). This phenomenon hollows out the intrinsic economic and existential value of the worker and reduces the economic value previously attributed to the cognitive work of human beings (Fuchs, 2024; Cinar, 2026). It is part of the larger context of Marxist political economy, which describes this as a new enclosure (the privatisation and monetisation of the intellectual commons) (Cinar, 2026), and cognitive capitalism as the extraction of surplus value from distributed, networked human creativity (Fuchs, 2024; Cinar, 2026; Bilandzic, 2023).

The curvature of emotional responsiveness is an integral component of HCI. HCI has now grown beyond usability to include the richness of user experience, including affective, emotional involvement (Flores, 2023). The findings reveal that affective responses are important factors that influence behaviours and user trust (Glickman & Sharot, 2025). Implementing emotion recognition capabilities enables the organisation to better analyse behaviours and dynamic emotions of interactions, thereby facilitating the creation of adaptive voice and language models that represent user personality in interaction (Flores, 2025a).

Based on the control-value theory of achievement emotions, emotions were hypothesised to be directly shaped by the learners' control appraisals, which affect core cognitive processes (Pekrun, 2024). This model is used in the current research on affective learning (Lin et al., 2023; Yuvaraj et al., 2025). In the context of HCI, as discussed above, personalised education systems based on the emotional profile of a single person become key (Flores, 2025b). Affective systems should not be limited to pre-coded/pre-designed responses, but should also recognise individualistic and unique emotional lines, reducing the biases found in the dataset that are generally present in deep learning systems (Mattioli & Cabitza, 2024; Shah & Sureja, 2025).

Figure 1:

The Curvature of Affective AI and Emotional Intelligence Protective Shield Framework



Note. *Conceptual mapping of the curvature of affective AI, algorithmic integration velocity, unaugmented cognitive labour depreciation, and the protective shielding effect of Emotional Intelligence (EI) and Perceived Social Support (PSS).*

To put it simply, the faster AI can do work, the sooner human cognitive labour loses value. However, people with high EI can harness perceived social support to build an adaptive buffer zone and maintain a level of subjective well-being beyond the levels of technological disruption, as these levels are not yet explored in AI operational efficacy.

The capacities to perceive, use, understand, and regulate emotions, both one's own and those of others, for adaptive functioning, as theorised by several empirical traditions (Flores, 2026; Flores, 2025b), are termed emotional intelligence (EI). EI has roots in earlier models that focused on the processing of abilities and has also been extended into trait-based models that incorporate personality, motivation, and social behaviour (Flores, 2026; Flores, 2025b). All of these traditions show a consistent pattern of stronger links between higher EI and lower rates of burnout, greater self-efficacy, more extensive social networks and more positive subjective well-being, especially in situations where stress and uncertainty are high (Flores, 2026; Flores & Luna, 2024; Flores, 2025b).

Perceived Social Support (PSS) refers to the individual's perception that they can rely on social network support and serves as an important mediational mechanism between EI and well-being (Flores, 2026). People with higher EI more effectively decipher social signals to communicate their needs and develop relationships that provide valuable, mutually rewarding support (Flores, 2026). Social support from peers, mentors and institutional supports is an important, but psychologically protective resource in times of technological upheaval and academic pressure (Flores & Luna, 2024; Pekrun, 2024). The introspective elements associated with success (such as intellectual humility, self-reflection, and receptiveness to feedback) have also been posited as important socio-cognitive traits connected with achievement and EI, indicating that EI cannot be separated from cultivation of other socio-cognitive values (Flores & Luna, 2023).

Methods and materials

The study is mixed-methodological research that combines a systematic literature review and a quantitative analysis based on the Partial Least Squares Structural Equation Modelling (PLS-SEM) approach (Acemoglu & Restrepo, 2019; Flores, 2026). The dual approach links macroeconomic aspects of AI adoption with the microeconomic psychological aspects, allowing triangulation at various levels of analysis (Acemoglu & Restrepo, 2019; Flores, 2026).

Literature Review & Data Synthesis

This step includes the systematic literature review and macro data synthesis. The review aimed to critically synthesise and analyse the current literature on the interplay between EI, affective technologies, and subjective well-being, particularly as AI is becoming more deeply embedded in daily life (Flores, 2025b; Yuvaraj et al., 2025). A systematic search process was carried out on the selected academic databases: Web of Science, Scopus, PsycINFO and Google Scholar, using the following search terms: emotion recognition, affective computing, cognitive capitalism, HCI, emotional intelligence, and subjective well-being (Flores, 2025b; Yuvaraj et al., 2025). Studies were included only if they were peer-reviewed, published in the last ten years, and used an empirical method, particularly a quantitative or mixed method (Flores, 2025b; Yuvaraj et al., 2025). Moreover, enterprise LLM adoption and productivity data across the population were aggregated from well-respected economic research in order to set the macroeconomic backdrop for the study (Dehouche, 2025; Hui et al., 2024; Noy & Zhang, 2023).

Structural Equation Modelling (PLS-SEM)

The primary empirical assessment is to examine the psychological buffering role of Emotional Intelligence (EI) against academic burnout and technological anxiety (Flores, 2026). A convenience sampling method was used to collect data from 623 university students (42.4% male and 57.6% female; 18-24 years of age) in emerging technology hubs (Flores, 2026). The sample was distributed across a range of institutional settings with high rates of AI uptake, growing gig economy involvement, and high levels of undergraduate exposure to algorithmic tools (Flores, 2026).

The research model is based on three major latent constructs: Emotional Intelligence (EI), Perceived Social Support (PSS) and Subjective Well-Being (SWB) (Flores, 2026). EI was operationalised by a validated scale drawing of 33 items based upon existing trait EI frameworks (Flores, 2026). PSS was assessed with a 12-item multidimensional perceived support scale, and SWB was determined by a composite of validated scales of positive affect and life satisfaction (Flores, 2026). SmartPLS 4 was used to perform the statistical analysis (Hair et al., 2019; Henseler et al., 2015). Stage one consisted of assessing the construct reliability by Cronbach's alpha and Composite Reliability (CR); all values were at or above the threshold of 0.80 (Hair et al., 2019; Henseler et al., 2015). The Average Variance Extracted (AVE) values were found to be above 0.50, confirming convergent validity, and the Heterotrait-Monotrait (HTMT) ratio criterion with values lower than 0.85 confirmed discriminant validity (Hair et al., 2019; Henseler et al., 2015). Bootstrapping was used to perform hypothesis testing with N = 5,000 resample iterations and to obtain robust non-parametric significance estimates for direct path and mediated path coefficients (Hair et al., 2019; Henseler et al., 2015).

EQ 1: STRUCTURAL MODEL EQUATION

$$\eta_{SWB} = \beta_{EI \rightarrow SWB} \cdot \xi_{EI} + \beta_{PSS \rightarrow SWB} \cdot \eta_{PSS} + \zeta$$

*[**Method Equation 1**.- Where η represents endogenous constructs, ξ represents exogenous constructs, β represents path coefficients, and ζ is the structural error]*

Analysis Results

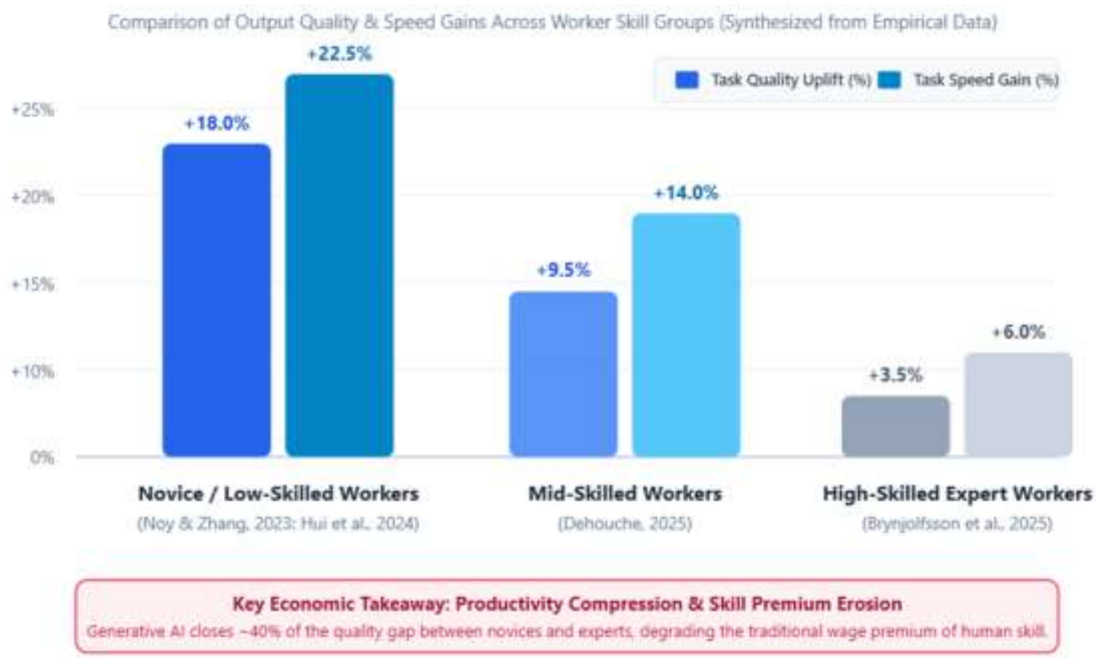
Macroeconomic Data: Enterprise Adoption and Productivity Asymmetry

The theoretical enclosure of cognitive labour is paralleled by the staggering speed of enterprise AI adoption (Dehouche, 2025; Noy & Zhang, 2023). A pattern of strong structural embedding into work routines in education and the corporate world is evident in the analysis of population-level data for 2022–2024 (Dehouche, 2025; Noy & Zhang, 2023). Generative AI is not an emerging and experimental technology; it is the primary communication medium used in financial analysis, public relations, legal drafting and academic writing (Dehouche, 2025; Noy & Zhang, 2023).

Importantly, the productivity benefits are concentrated very unevenly, creating significant disruptions of the existing market for human capital pricing (Noy & Zhang, 2023; Brynjolfsson et al., 2025; see Figure 2).

Figure 2:

Comparison of Output Quality & Speed Gains Across Skill Groups



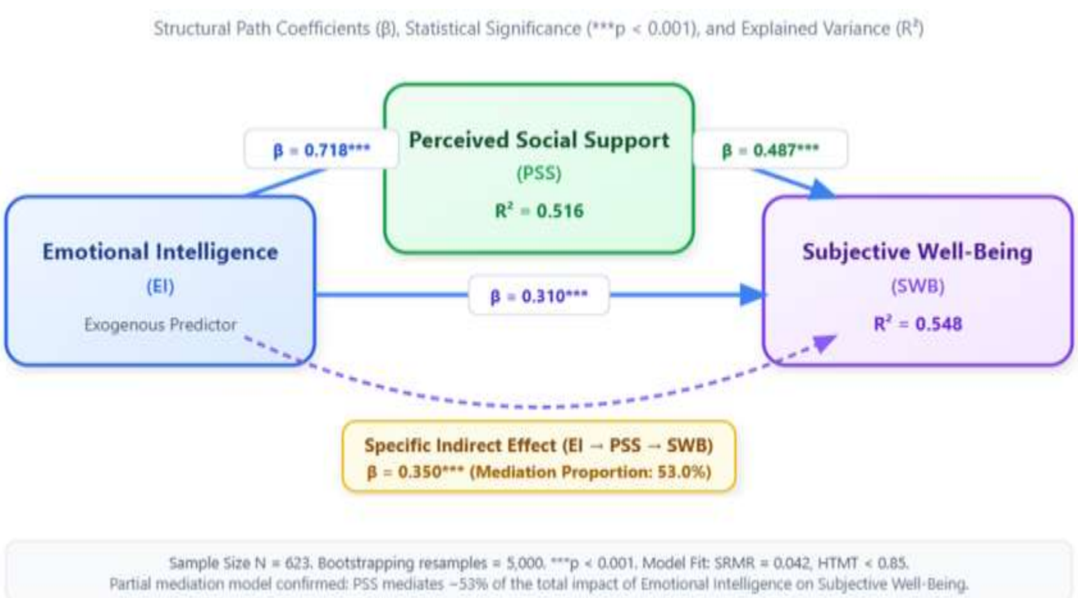
The experimental evidence presented in the real world shows that generative AI is a great equaliser that has a significant impact, particularly at the level of novice and low-skilled workers, with quality improvements of up to 40% compared to experts, and speed improvements of +22.5% (Noy & Zhang, 2023; Brynjolfsson et al., 2025). This narrowing of the skill premium is a direct structural challenge to the traditional wage premium and pushes highly skilled workers to serve only as editors, liability absorbers and alignment-checkers of the algorithmic product, not as primary cognitive producers (Hui et al., 2024; Brynjolfsson et al., 2025; Flores & Luna, 2024).

Furthermore, information from online labour markets suggests that measurable downward pressure on earnings can be seen in certain task categories where AI has been introduced within quarters after its implementation, and this process could systematically compromise the economic viability of knowledge-worker jobs, defined as those tasks where AI can be implemented. The measurement model yielded high reliability for each construct, as shown in Figure 2.

Thus, Cronbach's alpha was above 0.85, and the reliabilities of all the composites (CR) were above 0.88, indicating high internal consistency, in excess of the recommended 0.80. Convergent validity was established, with the average variance extracted (AVE) greater than 0.52 for each construct. All inter-construct ratio HTMT ratios were less than 0.85, indicating discriminant validity. The results from four path effects of PLS-SEM showed that all direct and mediated path effects were statistically significant when tested with bootstrapping (N = 5,000) at the 0.05 level of significance. The findings align with the research positioning of Emotional Intelligence (EI) as an important protective psychological factor in high-tech disruption contexts. The strongest result is the EI → PSS path ($\beta = 0.718$, $p < 0.001$), suggesting that people who have high EI have significantly better abilities to perceive available support, build supportive relational networks, and communicate their needs in a manner that is likely to create meaningful social resources (see Figure 3).

Figure 3:

Structure path coefficients



Note: Final Partial Least Squares Structural Equation Model (PLS-SEM) with the path coefficient (β), p-values (< 0.001), R^2 explained variance (PSS $R^2 = 0.516$; SWB $R^2 = 0.548$) and specific indirect path (β = 0.350; mediation proportion = 53.0%).

As a result, the pathway between the two was mediated by PSS (β = 0.487, $p < 0.001$); EI also had a substantial and significant direct effect on SWB (β = 0.310, $p < 0.001$), which supports a partial mediation model. The indirect effect of EI on SWB through PSS was fully standardised at β = 0.350 ($p < 0.001$), representing a significant portion of the total effect of EI on SWB (β = 0.660), and accounting for about 53% of the total EI–SWB relationship.

Conclusion

This study delivers a critical synthesis of macroeconomic automation trends (Acemoglu & Restrepo, 2019; Noy & Zhang, 2023; Brynjolfsson et al., 2025; Eloundou et al., 2023). The mathematical commodification of routine cognitive tasks is an effectively irreversible process within the current political-economic framework as shown by the asymmetric productivity data presented in Section 4.1 (Noy & Zhang, 2023; Brynjolfsson et al., 2025; Eloundou et al., 2023). The "human capital" edge, which represents the "natural" expertise and experience accumulated over time by humans, is coming to an end in settings where LLMs can generate similar content in seconds or minutes at almost zero additional cost (Dehouche, 2025; Hui et al., 2024; Cinar, 2026).

The issue of what is irreducibly human becomes not only a philosophical one but also a pressing one in this context (Flores & Luna, 2024; Flores, 2026). Indeed, the results of the PLS-SEM in this study support this hypothesis and others that have been previously put forward (Flores, 2026) Emotional Intelligence is unique, in that it is an embodied, relational, and context-sensitive process that cannot be reliably algorithmically replicated (Flores & Luna, 2024; Flores, 2026). Given that affective competencies (empathy, interpersonal attunement, ethical reasoning, and ability to build and maintain genuine human relationships) are strongly and statistically robustly correlated with EI and subjective well-being (Flores, 2026; Flores, 2025b), the future of human comparative advantage in an AI-driven world rests with these competencies.

Although AI can create large amounts of data and produce contextually coherent content (Flores, 2025a; Flores & Luna, 2024), it certainly cannot provide the emotional connection, lived-in context, and moral responsibility needed to develop meaningful social support systems (Flores, 2023; Glickman & Sharot, 2025). Research suggests, in fact, that AI systems that are not used with careful consideration can, to an extent, bias human judgements – in a way that can be measured – and can backfire on the emotional intelligence that these systems rely on (Glickman & Sharot, 2025). This requires immediate and critical investigation of the ethics of affective technologies: systems need to be designed explicitly to take human emotional growth into account, not to maximize engagement or measures of productivity (Mattioli & Cabitza, 2024; Shah & Sureja, 2025; Flores, 2025b).

Technologies that span from HCI to robotics to educational platforms need to be more than task-execution engines – they must be emotionally intelligent, and truly complementary to human EI, not pushing for cognitive passivity or algorithmic dependency (Flores, 2023; Flores, 2025b; Yuvaraj et al., 2025; Lin et al., 2023). Systematic review evidence for the field of affective computing in education shows that the adoption of a system that is capable of smartly responding to affective feedback results in better immediate performance on the task, as well as better long-term motivational dispositions and academic resilience (Yuvaraj et al., 2025; Lin et al., 2023), which are precisely the skills most critical for success in a labour market in the process of transformation (Pekrun, 2024; Flores, 2026).

This requires a change in mindset not only in the practice of corporate governance, but also in the way education is carried out (Glickman & Sharot, 2025; Dehouche, 2025; Preston, 2024; Cinar, 2026; Chaudhary, 2024; Marey et al., 2024; Fuchs, 2024; Mattioli & Cabitza, 2024). Ethical systems need to be created, such as mechanisms of transparency, data provenance, and audit, to protect against the 'black hole' extraction of cognitive and affective labour without consent or compensation, as AI systems feed on human interaction for continuous improvement of their model of human behaviour (Preston, 2024; Cinar, 2026; Chaudhary, 2024). The opacity of 'black box' AI systems is a structural threat to individual livelihoods, and to the collective epistemic commons (Chaudhary, 2024; Marey et al., 2024; Fuchs, 2024). Such regulatory transparency, is thus not a "sideline" but a condition of the very existence of AI systems used in educational contexts (Chaudhary, 2024; Mattioli & Cabitza, 2024).

Especially in education, there is a need to shift away from rote learning preparation of cognitive tasks and towards targeted and structured development of emotional intelligence, interpersonal empathy, critical digital literacy and adaptive psychological resilience (Pekrun, 2024; Flores, 2025b; Flores & Luna, 2023; Luna et al., 2026; Ocaña-Garzón & Mejía, 2021). Self-awareness and intellectual humility, which were identified as important introspective abilities for sustainable academic success, are even more important in a context where external algorithmic feedback remains constant and influences learners' self-models (Flores & Luna, 2023). This affective dimension also needs to be addressed in teachers' digital competence: if teachers themselves have not developed the EI in the digital environment, it will be difficult for them to scaffold their students' affective learning (Luna et al., 2026; Ocaña-Garzón & Mejía, 2021). This also affects LLMS, as they are perceived by users as overly confident machines that are often certain even of their errors, which creates mistrust among users.

These results in AI being perceived as aggressively taking over the cognitive sphere, while the economic and psychological value traditionally given to human labour is being systematically and irremediably undermined (Acemoglu & Restrepo, 2019; Brynjolfsson et al., 2025; Eloundou et al., 2023; Hui et al., 2024; Fuchs, 2024; Cinar, 2026; Preston, 2024). The marriage of affective technologies and generative models has begun a structural rejection of the human worker in routine cognitive work, and a massive societal, institutional, and individual adaptation is required (Fuchs, 2024; Cinar, 2026; Preston, 2024).

However, as this study strongly confirms, Emotional Intelligence provides a very powerful protective barrier against job market risk (Flores, 2026; Flores & Luna, 2024; Flores, 2025b; Flores, 2023; Flores, 2025a; Glickman & Sharot, 2025). High EI helps individuals continue to flourish psychologically even in high-disruption environments ($\beta = 0.660$ total effect, $p < 0.001$), and helps mobilise perceived social support ($\beta = 0.718$, $p < 0.001$) (Flores, 2026; Flores & Luna, 2024; Flores, 2025b). Future Human–Computer Interaction is not the struggle of humans to keep up with the power of computation, but rather the creation of adaptive and transparent systems which are sensitive to human affective complexity and to respect for the intrinsic complexity of the human being (Flores, 2023; Flores, 2025a; Glickman & Sharot, 2025).

Therefore, creating sustainable progress requires building ethical regulatory architectures that resist the pure commodification of human perception (Preston, 2024; Cinar, 2026; Chaudhary, 2024; Pekrun, 2024; Yuvaraj et al., 2025; Lin et al., 2023; Flores, 2025b; Mattioli & Cabitza, 2024; Shah & Sureja, 2025), the reorientation of missions in educational institutions towards the systematic development of affective competencies and relational skills (Pekrun, 2024; Yuvaraj et al., 2025; Lin et al., 2023; Flores, 2025b), and the recognition of emotionally intelligent design, not merely as a luxury but as a duty on the part of the developers of AI (Mattioli & Cabitza, 2024; Shah & Sureja, 2025). The trust of the end user (the human) is often overlooked, especially in corporate settings; on the technological side of AI (the computer), these systems should not be perceived as an extractive engine but rather as an augmentative resource for human flourishing, resisting not only the enclosure of the human mind by algorithms but also the corporative actions of the distinctive owners of such technologies.

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