Excessive AI Use: Effect on Perceived Self Efficacy and Self-Concepts Clarity

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Abstract

This investigation focuses on the psychological effects and motivational trends that result from using AI tools within educational and occupational frameworks. With 151 participants, this study explored relationships between variables like frequency of AI use, dependency, AI use motivation (both intrinsic and cognitive engagement), and self-concept clarity. AI has begun to be integrated into learning and working environments, and there is a need to look more closely at how it may affect one's sense of self and user motivation. A structured questionnaire was used to collect data from 151 participants, measuring the frequency of AI use, dependence, intrinsic motivation, cognitive involvement, and self-concept clarity. Ratings were recorded on a five-point Likert scale (1-5). Data was analysed using SPSS, including descriptive statistics, reliability testing (using Cronbach's Alpha), exploratory factor analysis (EFA), and multiple regression analysis. The results showed strong positive associations between intrinsic motivation, AI confidence (R^2 = 0.930), and cognitive engagement (R^2 = 0.626). Intrinsic motivation, however, was a negative predictor of self-concept clarity (R^2 = 0.444), meaning that the more motivated and confident users are in using AI, the less clear their self-perception could be. This paradox underscores the dual capacity of AI to enhance productivity whilst immensely complicating the process of self-identification and self-development. People interact with AI with dynamism, self-assuredness, and a sense of agency. However, overreliance on AI could hinder one's ability to distinguish oneself. These results underscore the psychological burden that AI usage could carry and support the need for students and professionals to design and apply thoughtful and intelligent approaches in balancing different aspects of AI.

Keywords: *Artificial Intelligence, Intrinsic Motivation, Cognitive Engagement, Self-Concept Clarity, AI Dependency, Psychological Effects, AI in Education.*

Introduction

Background of the study

AI does not simply boost productivity and improve decision-making as its impact cuts across emotional and relational dimensions of technology. With the relentless advances of AI and automation, the focus of the technology interaction has shifted from the behavioural elements of the user experience model to the deeper psychology and motivation (Holmes et al, 2019). The scope of modern AI is no longer restricted to automation as it can learn independently, assess intricate datasets, and conclude with minimal human engagement (Holmes et al., 2019). Questions related to users' mental focus, drive, and sense of self are emerging as the adoption of these tools is indisputable. A description for this result is not available because of this site's robots. Theoretical considerations Drawing on Self--Determination Theory (Ryan & Deci, 2000; Deci & Ryan, 2012) and Social Cognitive Theory (Bandura, 1997), our study analyses the impact of AI tools on autonomy, competence and self-efficacy.

Such research seeks to link self-determination and social cognitive theories related to autonomy, competence, engagement, and learning, with the outcomes being identified as motivational factors (Bandura, 1997; Deci & Ryan, 2012). The motivation of the AI is to encourage motivation and cognitive engagement through customised learning and adaptive feedback in different aspects (Wang et al., 2021; Joo et al., 2021). Psychologists have argued that AI positively affects students' motivation and cognitive engagement. Nevertheless, some sceptics fear that this risky radicalisation could cause various forms of identity diffusion as individuals began to outsource essential parts of their capacity for creative and critical thinking to technological devices (Turkle, 2011; Krüger & Jahn, 2021; Orben et al., 2020). This research aims to examine this relationship at the level of psychosocial determinants that influence the degree of AI use for intrinsic motivation, cognitive engagement, self-assessed clarity, and social assistive technology confidence.

Study Objectives

This study looks at the influence of AI tools on individuals' internal motivation, concentration, self-efficacy, confidence, and the self-concept in the workplace and academia.

Significance of the Study

In order to address these concerns, there should be more attention paid to the psychological complexities of AI use . These tools are capable of increasing motivation and perceived competence, but they also have the potential to disrupt self-identity and self-continuity. This contradiction shifts the focus of the conversation around digital dependency regarding AI to something more profound than just productivity. In these situations, it helps to know how to regulate and develop AI systems. Particular attention should be paid to how these systems shape identity in learning and working contexts.

Literature Review

AI Tool Usage in Educational and Professional Contexts

Implementing Artificial Intelligence (AI) technologies into education and the workplace is growing as they aid in writing, analysing data, making decisions, and facilitating adaptive learning. The tools in question can streamline processes and improve productivity. However, scholars are now investigating the cognitive and psychological effects of such tools on users (Lai, 2021; Holmes et al., 2019; Wang et al., 2021).

Increased use of AI is linked to enhanced academic self-management and engagement. Intelligent tutoring systems, for instance, adapt to learner availability and content pace, which is argued by Lai (2021) to promote independent learning. Focusing on the learner helps streamline content, supporting learning and facilitating deeper understanding (Holmes et al., 2019). These automation-focused AI tools promote efficiency and help reallocate cognitive resources toward more complex mental tasks. According to Adityaksa and Suyoso (2025), AI aids in organizational decision-making and workflow streamlining. Nevertheless, the precision and volume of AI tool applications differ significantly from one domain to another. Other research underlines the (positive) behaviour reinforcement that results from habitual AI use; according to this view, repetitive use of AI functions builds up familiarity and trust (Buçinca, 2024; Hein et al., 2024). Nevertheless, there are concerns over the potential dangers of dependency. As Acosta-Enriquez et al. (2025) pointed out, overreliance on AI technology, particularly in teaching situations, can induce excessive cognitive load and critically under stimulate the thinking skills of intellectually demanding students. Such concerns highlight the need to consider further how motivation and other psychologically-rooted factors intersect with dependence on AI technology.

Intrinsic Motivation and AI

Intrinsic motivation refers to the native tendency to engage in activities that are satisfying in themselves rather than for their effects (Deci & Ryan, 2012). AI systems will likely mediate this motivation to learn in educational and work contexts. Multiple studies indicate that AI systems for autonomy and personalised learning goals design increase the intrinsic motivation to interact with users (Ryan & Deci, 2000; Joo et al., 2021). For instance, in the education domain, adaptive system also provides personal feedback and learning paths to develop competence and curiosity for self-initiated engagement (Wang et al., 2021; Lee & Hwa, 2021). According to Jia and Tu (2024), personalisation and quality feedback in AI-powered environments can enhance the perceived relevance, leading to better intrinsic motivation levels. This is consistent with Self-Determination Theory, in which autonomy and competence are integral motivational elements. Analogous results have been reported in professional settings, wherein AI technologies that respect users' decision-making autonomy and offer timely insights can enhance motivation and confidence (Naiseh et al., 2025).

However, work-related motivation in the workplace frequently combines with instrumental goals such as efficiency and performance consequences, which could attenuate the purely intrinsic nature of engagement. This contrast points to one crucial difference: while AI in the educational context typically seeks to encourage intrinsic motivation for exploration and learning, work contexts are more concerned with productivity improvement, potentially leading to more extrinsically motivated evaluative attitudes. It is argued that contextual factors like ethical consideration, trust and perceived purpose of the AI incentive motivate as well. In both of these areas, motivation is influenced by AI design and the broader psychological and organisational context (Seo et al., 2024).

AI and Cognitive Engagement

Cognitive engagement is an individual's mental exertion and strategy for a given task. In educational psychology, cognitive engagement predicts learning, problem-solving, and mastery of skills at greater depth (Sweller, 2011). AI tools have been demonstrated to impact cognitive engagement by intensifying and sometimes suppressing users' cognitive processing. The relation of AI tools to users' mental attention and processing styles is particularly of interest to sociologists and psychologists. AI in schools can free up mental resources by relieving students from mundane tasks. Holmes et al. (2019) suggested that capturing deep attention because of the thoughtful structuring of the AI could foster thinking by automating lower-order tasks and interspersing these with reflection-promoting thinking stimuli that enhance subsequent thoughts. Also, Grinschgl and Neubauer (2022) consider AI tools to be extensions of human cognition. Therefore, they view them as enabling distributed cognitive systems as our biological and technological tools co-create understanding. Despite its advantages, there are increasing concerns about overdependence on AI. Carr (2010) was concerned about automation fostering "shallow thinking," where users become too reliant and stop engaging actively. Gerlich (2025) studied the cognitive offloading bias associated with AI tools, warning that habitual use may erode independent reasoning and memory retention over time. These effects may be powerful in work contexts that value rapid and efficient processing over reflective cognition. By contrast, educational AI tools may be designed more intentionally for enhancing active learning, metacognitive reflection, and cognitive persistence. As humans make sense of their experiences in the world around them, not least through new learning, they can be said to do so through actively building cognitive schemas that allow them to make sense of their experiences (Bruner,1966). This indicates a discrepancy in results: while AI's potential to minimise cognitive load benefits both settings, education systems tend to promote meaningful interaction, which can be resisted through the over-automation of workplace environments.

Ethical Awareness and Attitudes Toward AI

With the growing adoption of AI tools in daily routines and workflows, the ethical attention associated with their implementation has come to the forefront. AI raises ethical issues such as bias, a lack of algorithm oversight, inappropriate use, and the societal costs of automation dependence (Clark et al., 2019; Rakowski et al., 2021). As AI features are incorporated into everyday tasks, ethical consciousness and user perception have a pivotal impact on the adoption, trust, and responsible use of AI. These issues are evident in educational and clinical settings, but have distinct presentations and consequences. In educational environments, attention is frequently focused on Academic Integrity, data privacy and fair use. For example, Choung et al. (2022) reported that individuals scoring higher in ethical literacy will be more likely to evaluate AI advice with care and discretion. Ahmed (2024) also observed that when moral principles were included in higher education AI policies, students demonstrated more constructive and thoughtful usage of the AI.

On the other hand, moral issues in the workplace tend to revolve around job substitution and the monitoring and automation of decisions without people's direct involvement. Frenkenberg and Hochman (2025) found different emotions of employees towards AI, depending on whether they experienced the technology as enhancing or threatening. Positive sentiments toward the potential implications of AI were related to an increase in self-efficacy and acceptance, wherein fear regarding job loss or identity erosion resulted in resistance and distrust (Priyansh & Saggu, 2025). These opposing reactions demonstrate the contextual nature of AI ethics. If educational users usually conceptualise ethical awareness as contributing to responsible learning and growth of the individual, professionals seem to perceive it as balancing efficiency against existential matters.

Crucially, ethical consciousness is a mediator of attitudes to AI and a predictor of user confidence. Bewersdorff et al. (2024) reported that, for any given domain, a higher ethical literacy level of an individual was associated with more confidence in the ability to use AI responsibly. Naiseh et al. (2025) further stated that this ethical base can empower users for an increased sense of control and minimise some degree of technological helplessness.

Identity and Self-Concept Clarity in AI Use

An emerging issue in the psychology of AI use is its potential to disrupt self-concept clarity. Since users may stop using their thinking and creating while using AI systems, the price of these changes is debated regarding personal identities, authorship and agency (Turkle, 2011; Krüger & Jahn, 2021). Artificial intelligence algorithms that provide individualised feedback, task frameworks, and even author content can prompt learners to wonder about the source of their insights and the authenticity of what they contribute. Hutson and Barnes (2025) suggest that students who draw frequently upon AI-generated outputs may experience a disruption to their understanding of self, where they are uncertain about the originator of specific ideas. Farah et al. (2024) also add that students who live in AI-enhanced learning situations posit themselves as part of these algorithmic systems instead of independent thinkers.

It seems this is particularly the case in professional environments. Veliev (2024) and Galsgaard et al. (2022) report that engaging in AI-assisted collaboration tends to overshadow the individual's sense of value in the work. This is similar to the work of Orben et al. (2020), who pointed out that the digital age has made them prone to feeling fragmented about themselves, especially the youth. In the professional world, the more they use AI to assist them in making decisions, writing, and analysing information, the more they start to doubt the reasoned conclusions they arrive at and the degree of association they have with what they do. This tends to lower the self-appraisal, particularly when the AI is being assessed and not the person using it. Fujigaki (1993) and Galsgaard et al. (2022) observed the sense of self-estrangement and self-devaluation when personal input is overshadowed in AI-mediated, collaborative work.

Other literature suggests there are conditions under which AI may be associated with increased self-concept clarity. Jo et al. (2024) and Morales-García et al. (2024) claim that end users are more reflective about their competencies, values, and goals because of metacognitive or self-assessment features in structured reflective systems. In these situations, the systems assist users with self-reflection and identity development. However, user engagement and AI design are critical to materialize. Two distinct worlds are noted. Compared to professional realms that tend to focus solely on efficiency and suppress personal voice and reflection, educational domains might offer more opportunities to AI for identity work (e.g., feedback, skill development, reflection) activities. This is more likely to widen the schism: work, not school, becomes the site for cultivating a more fragmented or externally driven identity.

Research Methodology

This study analysed the psychological effects of AI tools deployed in the workplace and during training using quantitative research techniques. Respondents were gauged using self-responded, formatted questionnaires as part of the research. These questionnaires included the generic "demographics" section and thirty items to assess various AI usage and integration aspects. The respondents rated the items using a 5-point Likert scale ranging from "1," which indicated "Strongly Disagree," to "5," which indicated "Strongly Agree." Responses to negatively phrased questions were reversed so that any score above the midpoint was considered a positive agreement.

The sample included students, and the sample from the population was selected using convenience-based non-probabilistic sampling. 151 responses were received and considered valid, with the rest subjected to a rudimentary screening and marked as incomplete. While this may be a statistically acceptable sample size, convenience sampling remains an issue for external validity and generalisability. As such, the results should be interpreted with a fair amount of contextual consideration. Future studies should use a larger or stratified population sample to increase their representativeness and minimise bias.

Data analysis involved using SPSS, with the following techniques: descriptive statistics, reliability test (Cronbach's Alpha), exploratory factor analysis (EFA), correlation, and regression. Suitability of the dataset was confirmed through the KMO (Kaiser-Meyer-Olkin) test and Bartlett's Test of Sphericity. Assumptions of the regression, including normality, linearity, multicollinearity, and independence of the residuals, were checked for the validity of the results. The current study uses a rigorous quantitative method; however, it would be appropriate for future research to focus on triangulation or mixed methods to enhance the interpretation beyond statistical associations.

Table 1

Variable	Description
Frequency of Using AI Tools	Measures how regularly respondents interact with AI.
Areas of AI Use	Captures the diversity of AI applications across academic or professional tasks.
Dependency Level on AI	Reflects the extent to which users rely on AI to complete tasks.
Confidence in Using AI	Assesses users' self-efficacy and belief in their ability to effectively use AI tools.
Ethical Awareness in AI Use	Gauges understanding of bias, transparency, and responsible AI use.
Attitude Towards AI	Measures whether AI is viewed as beneficial or threatening.
Intrinsic Motivation	Assesses internal curiosity and interest in engaging with AI tools.
Cognitive Engagement	Evaluates the level of mental effort, focus, and deep thinking involved in AI-related activities.
Self-Concept Clarity	Assesses the consistency and clarity of one's self-perception, especially in relation to AI use.

Discussion and Analysis

Analytics from the self-administered questionnaires were used to identify the psychological traits for implementing AI for academic and professionally oriented tasks in 151 respondents. Regression modelling focused on measurement reliability and validity, relationships among variables, and predictive effects in this study.

Reliability and Validity

Reliability

Cronbach's Alpha assessed internal consistency. All composite scores showed internal reliability because none fell under the lowest cutoff value of 0.70. For instance, 'Dependency Level on AI' had an alpha of 0.875 while 'Confidence in Using AI' also displayed strong scores (alpha = 0.841). For the lowest alpha value, 'Attitude Towards AI' was also above the threshold at 0.760.

Validity

A further EFA also confirmed construct validity. This is "excellent" (KMO = 0.918). Also, a significant Bartlett's Test of Sphericity is found ($\chi^2 = 2688.842$, $p < 0.001$), and 66.01% of variance is extracted, further confirming the structural validity of this scale.

Descriptive Analysis

All constructs are measured with a five-point Likert scale. Each variable has high average scores, which means that affects for AI, motivation, confidence and engagement are mostly positive. What stands out, however, is Self-Concept Clarity, which had a low score. Nevertheless, from a theoretical standpoint, motivation and confidence with AI tools could result from high self-doubt. This can be referred to as a psychological paradox: that while people evaluate AI as more competent, it might also mean they are even more identity-diffuse as their judgments are instrumental and not an expression of who the person is, at least when being within contexts that focus on the output rather than the reflection.

Table 1
Descriptive Statistics

Variable	Mean	SD	Skewness	Kurtosis
Frequency of Using AI Tools	3.82	0.76	-1.136	2.837
Areas of AI Use	3.83	0.68	-1.183	3.71
Dependency Level on AI	3.66	0.79	-0.849	1.131
Confidence in Using AI	3.85	0.69	-0.973	2.867
Ethical Awareness in AI Use	3.75	0.68	-0.771	1.995
Attitude Towards AI	3.83	0.65	-1.191	4.593
Intrinsic Motivation	3.85	0.69	-1.044	3.205
Cognitive Engagement	3.9	0.66	-0.983	2.961
Self-Concept Clarity	1.34	0.79	0.857	1.137

Correlation Analysis

As the data were ordinal, Spearman's rho correlations were used to explore relationships between the primary psychological and behavioural variables employed. Strong, important and significant associations were found in several other categories. Most notably, Intrinsic Motivation was strongly positively correlated with Confidence in Using AI (ρ = 0.952, p < 01) (i.e., internally motivated individuals report being a skilled AI user). Just like above, the statistics describing the correlation of cognitive engagement with intrinsic motivation (ρ = 0.815, p <. 01) as well as with Confidence in Applying AI (ρ = 0.803, p <. 01) suggest that mentally engaged performers in AI are also highly enthusiastic and effective, which is a reflection of an integrated propensity. Interestingly, the Frequency of AI Use had moderate correlations with Confidence (ρ = 0.599), Intrinsic Motivation (ρ = 0.587), and Cognitive Engagement (ρ = 0.649). This supports the hypothesis that more frequent usage leads to psychological benefits. These findings support the model's theoretical basis in Self-Determination Theory, specifically concerning the relationship of motivation, engagement and perceived capability.

Table 3
Correlation Analysis

Variables	1	2	3	4	5	6	7	8	9
1. Frequency of Using AI Tools	1								
2. Areas of AI Use	0.616 **	1							
3. Dependency Level on AI	0.535 **	0.649 **	1						
4. Confidence in Using AI	0.599 **	0.648 **	0.659 **	1					
5. Ethical Awareness in AI Use	0.453 **	0.514 **	0.495 **	0.556 **	1				
6. Attitude Towards AI	0.528 **	0.521 **	0.546 **	0.598 **	0.490 **	1			
7. Intrinsic Motivation	0.587 **	0.633 **	0.677 **	0.952 **	0.533 **	0.580 **	1		
8. Cognitive Engagement	0.649 **	0.644 **	0.652 **	0.803 **	0.493 **	0.586 **	0.815 **	1	
9. Self-Concept Clarity	-0.574 **	-0.582 **	-1.000 **	-0.631 **	-0.485 **	-0.538 **	-0.628 **	-0.646 **	1

Regression Analysis

Based on these results, the predictive relationships among the variables were evaluated through regression analyses. It is worth mentioning that across multiple models, Intrinsic Motivation emerged as the strongest predictor. It explained a remarkable 93% variance in Confidence in Using AI (β = 0.965, p <. 001) and revealed that internal motivation and self-efficacy for AI tools are highly related. It also negatively predicted Self-Concept Clarity (β = -0.666, p <. 001), indicating that motivation is not only related to competence but may also contribute to reduced self-clarity. This paradox implies cognitive offloading or identity-diffusive effects when individuals deeply engage with AI systems.

Frequency of AI Use further significantly explained variance in intrinsic motivation (R^2 = 0.556) and cognitive engagement (R^2 = 0.626), as interest and mental participation increase with increasing use of the AI technique. Secondly, Cognitive Engagement was positively related to Confidence in Using AI (β = 0.853, p <. 001), strengthening the mental effort/perceived competence loop. As such, these findings align with self-determination and social cognitive theory, which emphasise learning potential from AI use while posing a risk for self-models.

These findings, particularly the very high value of R^2 (0.930), should be treated with caution. The argument is powerful and seems to have overfitting, particularly because of familiar scale measurements. In addition, since a self-report scale was used in this study, standard method bias (CMB) may be one issue. In further studies, the authors suggest researchers may run robustness checks (such as validity using split-sample validation; confirmatory factor analysis) and apply multi-method approaches to the collection of data (using behavioural logs or interviews), which would be likely candidates to cure potential CMB and test generalizability. The frequency of AI Use predicted Intrinsic Motivation (R^2 = 0.556) and Cognitive Engagement (R^2 = 0.626). Confidence in AI Use was highly predictable by Cognitive Engagement (R^2 = 0.728, β = 0.853).

Table 4
Regression Analysis

Hypothesis	**Independent Variable**	**Dependent Variable**	**R^2**	**β**	**p-value**	**Durbin-Watson**	**Outcome**
H1	Dependency on AI	Confidence in Using AI	0.478	0.691	< .001	1.712	Accepted
H2	Frequency of AI Use	Intrinsic Motivation	0.556	0.746	< .001	1.882	Accepted
H3a	Intrinsic Motivation	Confidence in Using AI	0.93	0.965	< .001	2.342	Accepted
H3b	Intrinsic Motivation	Self-Concept Clarity	0.444	-0.666	< .001	1.624	Accepted (Negative)
H4	Frequency of AI Use	Cognitive Engagement	0.626	0.791	< .001	1.974	Accepted
H5	Cognitive Engagement	Confidence in Using AI	0.728	0.853	< .001	1.918	Accepted

Key Findings

- Core variables like dependence, motivation, technology engagement, and AI usage frequency obtained excellent reliability with Cronbach's Alpha scores ranging from 0.760 to 0.875.
- EFA determined that the factors confirmed from the questionnaire had a distinct structure from one another, and the factors accounted for 66.01% of the total variance. This confirmed the validity of the measurement model and the theoretical structure of the questionnaire.
- AI tool usage frequency significantly predicted Intrinsic Motivation (R^2 = 0.556, β = 0.746) and Cognitive Engagement (R^2 = 0.626, β = 0.791). This indicates that the more AI tools are used, the greater the Interest displayed and mental focus observed.

- There was a strong positive relationship between Intrinsic Motivation and Self-Confidence ($R^2 = 0.930$, $\beta = 0.965$), and also self-concept clarity was negatively correlated with Intrinsic Motivation ($R^2 = 0.444$, $\beta = -0.666$), which indicates a psychological cost associated with AI usage.
- Engagement ($R^2 = 0.728$, $\beta = 0.853$) was predicted significantly by confidence in the usage of AI, which implies that greater mental effort directed to AI tasks is associated with higher self-efficacy perception.
- Spearman Correlation supports verification of the correlation Intrinsic Motivation and Confidence ($\rho = 0.952$), Intrinsic Motivation and Cognitive Engagement ($\rho = 0.815$), along with Cognitive Engagement and Confidence, confirms a tightly linked set of psychological constructs (and confidence).
- The data reveals these contradictory frameworks wherein AI loses focus on the user, AI facilitates motivation, focus, and confidence, but fractures the user's internal self-identity.
- There is a rise in motivation and self-efficacy but a decrease in self-identity clarity, which becomes more pronounced without self-reflective, non-AI interaction.

Conclusion and Recommendation

Conclusions

This paper examines the psychological effects of AI tool use in private and professional spheres, including using AI tools in personal life, teaching, and working spaces. In this study, the AI-related activities showed greater intrinsic motivation, engagement in self-perception, and in some cases self-perception bolstering. In psychology, such phenomena are explained by self-determination theory (Ryan & Deci, 2000) and social cognitive theory (Bandura, 1997).

The paradox of AI remains: motivation and confidence. AI-generated reflections paradoxically diminish self-concept. AI dependence strips personal autonomy and agency, which suggests greater bewilderment about self in the elusive and creative pursuits. Such self-fragmentation and over–reliance on technology issues were elaborated in engagement with the AI ecosystem (Krüger & Jahn, 2021; Orben et al., 2020).

Recommendations

- Tactics that promote self-sufficiency in an ‘AI-driven world’ while also being self-sustaining should include self-sufficient and personal effort tools. There should be more effort in using AI as opposed to passive use.
- Set against these influences, passive self-concept clarifying influences are self-anchored through journals, self-review, and practitioner self-review, which, in this case, sponsor review and contextual analysis, focusing on AI, facilitates more seamless integration.
- How one perceives oneself helps inform their interactions with intelligent systems. Therefore, programs should teach positive and strong technical self-efficacy with identity management, ethical self-reflection, psychological resilience, and well-being consideration when designing the programs.

- The lack of self-concept clarity causes the value of qualitative approaches like interviews and ethnographic studies to be better understood in the psychological and social impacts of AI in everyday life.
- Surveillance should focus on the psychological offloading, self-disorientation, and self-unawareness intervals which AI enhances, and implement adequate structures for interaction with AI systems.

The psychological impacts of AI on productivity and self-confidence are equally important aspects to consider. In AI's case, it is the same as the focus on identity, agency, and critical user engagement in the human-centred design that must be applied.

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