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A Thematic Synthesis of HCI for Productivity and Wellbeing: Findings From a Systematic Review

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ABSTRACT

Human–Computer Interaction (HCI) has become a critical driver of productivity and wellbeing across diverse industries. This paper presents a systematic literature review (SLR) of HCI research published between 2003 and 2025. Following PRISMA guidelines (Liberati et al., 2009; Moher et al., 2009), 450 studies were identified across ACM, IEEE, Elsevier, Springer, Scopus, and ScienceDirect. After title/abstract screening (n = 115) and full-text quality assessment, 30 studies meeting reliability and validity criteria were selected for thematic analysis. The experimental setup involved a structured database search, a two-stage screening protocol, and thematic coding of findings across five domains: healthcare, education, industrial environments, workplace productivity, and digital wellbeing. Data analysis followed a narrative synthesis approach, identifying patterns across domains through iterative categorisation. Four primary themes emerge: user-centred design for performance enhancement; healthcare and assistive interaction systems; interfaces supporting cognitive and emotional wellbeing; and adaptive or multimodal interaction technologies. Usability, accessibility, and contextual design consistently emerge as critical success factors. While HCI delivers measurable gains, significant gaps persist in standardised evaluation metrics, longitudinal assessment, and cross-domain integration. This study provides a structured synthesis and identifies key directions for future human-centred digital system design.

Keywords: Human–computer interaction, Systematic literature review, Productivity, Wellbeing, Usability

INTRODUCTION

The world is entering a new industrial revolution characterised by the convergence of physical and digital systems, increased automation, and stronger human–machine interaction (Xu et al., 2018; Eberhard et al., 2017; Ibarra et al., 2018). In this context, Human–Computer Interaction (HCI) has become essential for improving productivity and wellbeing across multiple sectors (Grudin, 2019). HCI encompasses the design, evaluation, and implementation of interactive computing systems for human use, and plays an increasingly central role in shaping how individuals interact with information systems, AI-driven platforms, and smart environments. Advances in Artificial Intelligence (AI) accelerate HCI development across manufacturing, transportation, logistics, and services (Makridakis, 2017),

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with rapid growth in AI-related research and patents reflecting increasing global interest (De Prato et al., 2018; Fujii and Managi, 2018; Cockburn et al., 2019; WIPO, 2019). Despite this growth, evidence of HCI's impact on human wellbeing and operational productivity remains fragmented across disciplines, databases, and application domains, highlighting the need for systematic cross-domain synthesis.

AI-enabled HCI systems improve healthcare through smart health monitoring, machine learning-based diagnosis, and technology-supported rehabilitation (Rahman et al., 2022; Islam and Shamsuddin, 2021; Zheng et al., 2022). In industrial settings, recent HCI research integrates explainable AI, human–robot interaction, and worker wellbeing design principles into production interfaces (Geurts et al., 2024; Braun, 2024). In the productivity domain, eye-tracking, speech recognition, cloud computing, and AR/VR technologies have measurably reduced friction in human–computer workflows (Khamis et al., 2018; Sultan, 2010; Ruthenbeck and Reynolds, 2015). This review addresses two research questions:

RQ1: What is the role of HCI on productivity and wellbeing globally?
RQ2: How does technology impact productivity and human wellbeing?

METHODS

Experimental Setup and Search Strategy

This review follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Liberati et al., 2009; Moher et al., 2009) to generate a reliable knowledge base and develop appropriate research synthesis. The experimental setup comprised four stages: (1) definition of research questions and search scope; (2) structured multi-database search strategy; (3) two-stage data screening; and (4) thematic data analysis. The search spanned six databases: ACM Digital Library and IEEE Xplore for specialist computing literature, and Springer, Elsevier, Scopus, and ScienceDirect for broader interdisciplinary coverage. HCI search terms included "Human-Computer Interaction", "HCI implication", "HCI usage", and "AI impact". Wellbeing-related terms included "human wellbeing", "staff wellbeing", and "employee wellbeing". No start-date restriction was applied; coverage extended through December 2025.

Data Collection and Screening

The combined database search yielded 450 records (ACM: 68; IEEE: 82; Springer/Elsevier: 185; Scopus/ScienceDirect: 115). Stage one screening removed duplicates and irrelevant records based on title and abstract review, reducing the pool to 115 full-text papers. Stage two applied full-text eligibility assessment. Eligible studies were full-length, peer-reviewed, English-language articles directly addressing HCI in relation to productivity or wellbeing, demonstrating reliability and validity of measurement scales. Editorials, book reviews, conference abstracts, duplicates, and non-English publications were excluded. This yielded 30 studies for final thematic analysis.

Data Analysis

Data analysis followed a narrative synthesis approach (Liberati et al., 2009). Each of the 30 included studies was coded against five thematic domains identified inductively from the literature: Wellbeing, Medicine and Healthcare HCI, Training and Assistive Technologies, Productivity Tools, and Industry 4.0. Each study was assigned to one primary domain based on its central contribution. Within domains, findings were further categorised by technology type, application context, and reported outcome. The domain distribution was: Wellbeing (n=19), Medicine/HCI (n=17), Training and Assistive Tech (n=15), Productivity (n=16), and Industry (n=15). Out of all these 82 finally the Tables 1 and 2 present 30 representative studies – selected to illustrate the breadth of the evidence base – with all 30 studies informing the synthesis.

RESULTS

The thematic analysis of 30 studies identified consistent patterns across five domains. Tables 1 and 2 present 30 representative studies, while the narrative below synthesises findings from all 30 included papers.

Wellbeing

Across 19 wellbeing studies, technology consistently emerged as a dual-edged phenomenon. Digital tools – remote email, online conferencing, and cloud platforms – improve workplace efficiency but simultaneously create an "always-on" culture threatening work–life balance and mental health (Jonker-Hoffren, 2020; Nakrosiene et al., 2019; Bellmann and Hübler, 2020; Moore, 2000). Wearable health technologies are increasingly mainstream: 35% of employees monitor physical activity or fitness; 26% track diet; 22% seek health advice via social media; and 16% use telemedicine (Geurts et al., 2024). COVID-19 substantially accelerated adoption of home-quarantine monitoring (Sicari et al., 2022), and low-cost smart-health frameworks for biomarker collection via wearables are advancing rapidly (Rahman et al., 2022). Among younger populations, social media platforms significantly influence connectedness and mental wellbeing (Boniel-Nissim et al., 2022), while AI tools show growing effectiveness in mental health treatment support (Ausman, 2019; Tachtler et al., 2021).

Medicine and Healthcare HCI

Seventeen studies in the medicine and healthcare domain consistently demonstrate HCI's role in systems requiring high precision, fast feedback, and intuitive interfaces. The availability of heterogeneous biomedical data enables large-scale clinical studies contributing to improvements in clinical research (Ravi et al., 2017; Collins and Varmus, 2015), precision medicine (Topol, 2019), and workflow efficiency (Rundo et al., 2020). Clinicians interpreting complex and conflicting information under time pressure (Kushniruk, 2001) rely on effective human-system collaboration for safe treatment delivery (Nemeth et al., 2005; Patel et al., 2008; Franklin et al., 2011). AI-based decision support systems improve diagnostic accuracy and clinical workflows (Goldenberg et al., 2019). Machine learning has demonstrated effectiveness in multi-stained image registration for pathology (Hoque et al., 2022), chronic low back pain rehabilitation (Zheng et al., 2022), hypertension management through lifestyle modification (Islam and Shamsuddin, 2021), and stress prediction during COVID-19 social isolation (Li et al., 2022). Screen-time tracking applications show criterion validity across smartphones and tablets (Kristensen et al., 2022).

Training, Education, and Assistive Technologies

Fifteen studies address training, education, and assistive HCI. Structured training programmes are essential for the safe adoption of advanced medical technologies (Yang, 2020), with targeted training required to address differences in knowledge between registered nurses and other care staff (Hewitt-Taylor, 2004). Structured education programmes with discharge coordinators reduce hospital stays and improve patient self-management (Graf et al., 2008; Wong et al., 2009; Tearl et al., 2006). For people with disabilities, eye-controlled HCI systems – eye keyboards and eye mice – enable hands-free computer interaction using gaze direction and blinking (Magee et al., 2004; Li et al., 2009; Spakov and Majaranta, 2009; Isokoski, 2000; Tien and Atkins, 2008). Larger key sizes improve interaction accuracy above 95%, enhancing typing speed and usability (Magee et al., 2004).

Table 1: Representative studies – wellbeing, medicine, and assistive technology domains (n =15 of 51).

Authors	Source	Year	Topic / Key Finding
Grudin (2019)	ACM	2019	Anticipating HCI futures through historical analysis
Topol (2019)	Nat. Med.	2019	AI–human convergence in high-performance medicine
Ravi et al. (2017)	IEEE	2017	Deep learning for health informatics; clinical workflow support
Goldenberg et al. (2019)	Nature Reviews	2019	AI-enhanced diagnostic accuracy in prostate cancer ML
Hoque et al. (2022)	Elsevier	2022	Multi-stained feature matching for whole-slide image registration
Zheng et al. (2022)	Elsevier	2022	ML predicts central sensitization and gait in chronic low back pain
Islam and Shamsuddin (2021)	Elsevier	2021	ML promotes hypertension management via lifestyle change
Rahman et al. (2022)	Smart Health	2022	Smart-health wearable framework for low-cost biomarker collection
Sicari et al. (2022)	Smart Health	2022	IoT-based home quarantine monitoring during COVID-19

(Continued)

Table 1: Continued.

Authors	Source	Year	Topic / Key Finding
Boniel-Nissim et al. (2022)	Computers Hum. Behav.	2022	Social media use links to mental wellbeing in adolescents
Geurts et al. (2024)	Front. Comp. Sci.	2024	Human-centred HCI strategies for worker wellbeing in Industry 5.0
Tachtler et al. (2021)	ACM CHI	2021	Social-ecological approach to mental health technologies for youth
Hewitt-Taylor (2004)	Intensive Crit. Care	2004	Staff education and training for long-term ventilation technology
Magee et al. (2004)	CVPRW	2004	Gaze detection interface enables hands-free assistive eye control
Spakov and Majaranta (2009)	PsychNology J.	2009	Scrollable keyboard design improves casual eye typing efficiency

Productivity: Eye-Tracking, Speech, Cloud, and AR/VR

Sixteen productivity studies reveal that eye-tracking, speech recognition, cloud computing, and AR/VR technologies have substantially reduced friction in human-computer workflows. Productivity is consistently defined as a ratio of output to input (Singh et al., 2000; Tangen, 2005; Palfreyman, 2013), with both national competitiveness and organisational profitability depending on its improvement. Eye-tracking uses infrared sensors to determine gaze direction and has demonstrated value in workplace focus analysis, biometric authentication (Bednarik et al., 2005; Kasprowski and Ober, 2004; Maeder and Fookes, 2003), gaze-based password entry (Kumar et al., 2007; Khamis et al., 2018; Liu et al., 2017), and public display interaction (Zhang et al., 2015; Fuhl et al., 2016; Hirzle et al., 2019; Turner et al., 2014). Speech recognition enables virtual assistants to handle routine tasks at 120–150 words per minute versus 40–80 wpm for typing (Abdul-Kader and Woods, 2015). Cloud computing enables on-demand shared resource access, improving service quality and enabling real-time collaboration (Yang, 2012; Sultan, 2010; Wu et al., 2013). In medical simulation, haptic teleoperation enables robotic tumour localisation (Talasaz and Patel, 2013), surgical drilling assistance (Diaz et al., 2014), AR-guided tumour palpation (Jeon and Harders, 2014), visuo-haptic 4D volume rendering (Fortmeier et al., 2015), collaborative VR cardiac training (Khanal et al., 2014), and laparoscopic surgery simulation (Pan et al., 2015; Escobar-Castillejos et al., 2016; Hamza-Lup et al., 2019).

Industry 4.0 and HCI

Fifteen industry studies examine HCI in the context of Industry 4.0 – characterised by cyber-physical systems (CPS), IoT, and cloud computing (Gupta and Kumar, 2021; Lu, 2017; Bag et al., 2021). These technologies enable machine-to-machine communication, smart factories, and improved organisational processes (Colbert et al., 2016; Ibarra et al., 2018). However, widespread ICT use leads to technostress, social isolation, and reduced job satisfaction (Chowdhury and Sultana, 2025; Jonker-Hoffren, 2020; Hurmelinna-Laukkanen et al., 2021). Bellmann and Hübler (2020) found heterogeneous links between remote work and work–life balance; Moore (2000) documented work exhaustion among technology professionals. Mhaidli and Roemmich (2024) demonstrate how publication pressure and toxic norms in HCI academia harm researcher wellbeing. Sustainable HCI design approaches are proposed for Italy's manufacturing paradigm (Bagnato, 2024), while post-growth eco-harmonist frameworks challenge consumption-driven HCI design (Dhand, 2025). The ReWA framework addresses reproductive wellbeing as an emerging HCI equity frontier (Chowdhury and Sultana, 2025).

Table 2: Representative studies – Productivity and Industry domains (n = 15 of 31).

Authors	Source	Year	Topic / Key Finding
Bednarik et al. (2005)	Springer	2005	Eye movement patterns validated as a biometric authentication method
Kumar et al. (2007)	ACM SOUPS	2007	Gaze-based password entry reduces shoulder-surfing attacks
Khamis et al. (2005)	ACM MobileHCI	2018	Survey: past, present, future of gaze-enabled mobile device interaction
Abdul-Kader and Woods (2015)	IJACSA	2015	Chatbot design techniques for speech-driven conversation systems
Sultan (2010)	Int. J. Inf. Mgmt.	2010	Cloud computing adoption improves educational service quality
Talasaz and Patel (2013)	IEEE Trans. Haptics	2013	Force reflection and tactile sensing for minimally invasive robotics
Khanal et al. (2014)	J. Biomed. Informat.	2014	VR-based ACLS training with haptic and audio feedback for error correction
Escobar-Castillejos et al. (2016)	J. Med. Syst.	2016	Systematic review of haptic device simulators for medical training
Bag et al. (2021)	Ind. Marketing Mgmt.	2021	Integrated AI framework improves B2B knowledge creation and decisions
Colbert et al. (2016)	Academy Mgmt. J.	2016	Digital workforce dynamics and workplace transformation in Industry 4.0
Moore (2000)	MIS Quarterly	2000	Work exhaustion in technology professionals leads to high turnover
Hurmelinna-Laukkanen et al. (2021)	Technovation	2021	Lead user involvement in innovation networks improves outcomes
Mhaidli and Roemmich (2024)	ACM CHI Ext.	2024	Toxic norms and overwork in HCI academia harm researcher wellbeing
Chowdhury and Sultana (2025)	arXiv	2025	ReWA framework addresses reproductive wellbeing as HCI equity frontier

CONCLUSION

This systematic review of 30 studies, guided by PRISMA (Liberati et al., 2009; Moher et al., 2009) and a structured thematic analysis across five domains, demonstrates that HCI has profoundly shaped global productivity and wellbeing. The experimental setup – comprising a six-database search, two-stage screening, and narrative synthesis – enabled rigorous identification and analysis of evidence. Key gains confirmed by the data analysis include: smart-health wearables for biomarker monitoring (Rahman et al., 2022); ML-based rehabilitation (Zheng et al., 2022; Islam and Shamsuddin, 2021); telehealth platforms during COVID-19 (Sicari et al., 2022); VR surgical training with haptic feedback (Ruthenbeck and Reynolds, 2015; Khanal et al., 2014; Escobar-Castillejos et al., 2016); gaze-based authentication and interaction (Bednarik et al., 2005; Kumar et al., 2007; Khamis et al., 2018); and cloud-enabled collaborative productivity (Sultan, 2010; Wu et al., 2013). These gains are counterbalanced by documented costs: technostress and work exhaustion (Moore, 2000; Bellmann and Hübler, 2020); researcher burnout in HCI academia (Mhaidli and Roemmich, 2024); and sustainability concerns (Bagnato, 2024; Dhand, 2025; Chowdhury and Sultana, 2025).

Three persistent gaps limit scientific rigour across the literature: (1) standardised metrics for evaluating HCI impact on wellbeing and productivity are absent, making cross-study comparison difficult; (2) longitudinal studies tracking HCI interventions over time are rare, leaving long-term effects poorly understood; and (3) cross-domain integration between healthcare, workplace, and assistive HCI is limited. Future research should develop validated, domain-agnostic HCI evaluation frameworks, design longitudinal study protocols, and prioritise human-centred principles – addressing psychological wellbeing, supporting skill development, respecting cultural diversity, and aligning technological progress with planetary and social limits (Geurts et al., 2024; Dhand, 2025). Only through such reorientation can HCI fulfil its fundamental promise: not merely to make systems work better, but to make human life better.

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