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Digital technology use and psychological well-being: a review of evidence and a causal framework for personalised decision support

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ABSTRACT

Digital information technologies (IT) have become deeply embedded in everyday life, transforming communication, education, work, and social interaction and raising pressing questions about their psychological consequences. This review synthesises current evidence on measurable IT-related factors (screen time, social media use, smartphone use, information overload, online social support, digital gaming, remote work, interactions with artificial intelligence, cyberbullying, and technology-related sleep disturbance) and their relationships with psychological well-being. It also surveys the statistical approaches used to quantify these relationships, including specification-curve analysis and multilevel modelling. The evidence indicates that associations between overall technology use and well-being are small in aggregate and highly heterogeneous across individuals and contexts, whereas cyberbullying and sleep disturbance show more consistent negative associations. Building on these findings, the paper proposes a causal framework for personalised decision support, in which recommendations are based on the expected effect of actually changing a person's digital behaviour rather than on observed correlations, and favour small, achievable changes that preserve the benefits of technology use. The review concludes that progress requires longitudinal, experience-sampling, and experimental designs, more consistent measurement of IT-related factors, and reporting of how sensitive findings are to modelling choices.

Keywords: psychological well-being; mental health; cyberpsychology; social media; artificial intelligence; causal modelling; personalised decision support

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Introduction. Smartphones, social media, artificial intelligence (AI), and other digital platforms have created an environment of near-constant connectivity, making the psychological consequences of human-IT interaction a pressing interdisciplinary concern [1], [2]. Cyberpsychology examines how digital environments shape cognition, emotion, behaviour, identity, and relationships. Its central question is no longer simply how much technology people use, but how, why, when, and under what conditions.

The relationship between technology use and psychological well-being resists simple cause-and-effect explanations [2]. Even reviews of largely the same body of research on social media reach different conclusions [3]. This cautions against uniformly positive or negative interpretations and suggests that differences in study design and measurement contribute to inconsistencies in the literature.

The spread of AI adds further psychological and ethical questions, including trust in technology, personal autonomy, privacy, cognitive dependence, and the long-term effects of interacting with intelligent systems [2], [4].

Aim of the review. This review aims to identify measurable IT-related factors (screen time, social media use, smartphone usage patterns, information overload, online social support, digital gaming, remote work, interactions with AI systems, cyberbullying, and technology-related sleep disturbance) and to examine their relationships with psychological well-being. It further seeks to evaluate the statistical approaches used to quantify these relationships and to identify the conditions under which technology use may enhance psychological well-being while minimising psychological risks. Building on this evidence, the review also aims to propose a causal framework for personalised decision support on digital behaviour.

Psychological Well-Being: Definition and Conceptual Development

Psychological well-being (PWB) is a multidimensional concept describing positive psychological functioning: how individuals evaluate their lives, maintain relationships, pursue meaningful goals, adapt to their environment, and develop their capacities. It is not merely the absence of psychological disorders. Contemporary approaches emphasise people's ability to cope with everyday stresses, realise their abilities, learn and work well, and contribute to their communities, and recognise that mental health is shaped by individual, family, community, and structural factors [5].

Two major theoretical traditions are particularly important in the study of well-being: the hedonic and the eudaimonic.

The *hedonic* perspective focuses on happiness, life satisfaction, positive emotions, and the relative absence of negative emotions. It strongly influenced the concept of subjective well-being (SWB), which Diener [6] described through three components: life satisfaction, positive affect, and negative affect.

The *eudaimonic* perspective, in contrast, considers well-being in terms of meaningful and effective psychological functioning rather than happiness alone. One of its most influential models was developed by Ryff [7], who identified six dimensions of psychological well-being: self-acceptance, positive relations with others, autonomy, environmental mastery, purpose in life, and personal growth. Ryff's model extended the understanding of well-being beyond happiness towards the broader question of what it means to function positively.

The two traditions are complementary rather than competing: hedonic measures capture how people feel about their lives, whereas eudaimonic measures capture how well they function. For research on digital technologies, this distinction matters, because a given digital activity may increase momentary enjoyment while having little effect on, or even undermining, longer-term functioning, and vice versa. The present review therefore uses psychological well-being in a broad sense that encompasses both dimensions.

Philosophical foundations. The concept of well-being (WB) has roots in ancient philosophy, which distinguished between a life based primarily on pleasure and one based on meaning, virtue, and the realisation of human potential. These ideas later informed the distinction between hedonic well-being, concerned with happiness and positive experience, and eudaimonic well-being, concerned with meaning, personal development, and positive functioning.

Conceptually, this early view can be summarised as:

$$WB = f(Pleasure, Meaning, Virtue). \quad (1)$$

Economic and industrial society. With industrialisation and economic development, well-being became increasingly associated with objective living conditions such as income, employment, housing, education, health, and material security. However, material prosperity alone does not fully describe psychological well-being, and research increasingly distinguished objective quality-of-life indicators from individuals' subjective evaluations of their lives.

This shift can be summarised as a move from

$$WB = f(Material\ conditions, Health, Social\ conditions), \quad (2)$$

towards

$$WB = f(Objective\ conditions, Subjective\ experience) \quad (3)$$

Psychological models of well-being. During the twentieth century, well-being became an important empirical subject in psychology. Diener [6] systematised subjective well-being, emphasising life satisfaction and emotional experience. Ryff [7] then proposed a multidimensional model, arguing that positive functioning involves substantially more than happiness. Keyes [8] further proposed a mental-health continuum ranging from languishing to flourishing, supporting the view that positive mental health should be studied as more than the absence of mental illness.

The multidimensional view can be represented conceptually as:

$$PWB = f(SA, PR, A, EM, PL, PG), \quad (4)$$

where: *SA* is self-acceptance; *PR* is positive relations with others; *A* is autonomy; *EM* is environmental mastery; *PL* is purpose in life, and *PG* is personal growth. This is an illustrative representation, not an estimated model.

This shift reflected a broader change in thinking about health and psychology. Earlier approaches often concentrated on a sequence of disease, diagnosis, and treatment. Researchers increasingly recognised that the absence of illness does not necessarily mean that a person is flourishing, which raised a broader question: what enables a person to function and live well? Psychology therefore began to study not only depression, anxiety, and other disorders but also happiness, life satisfaction, relationships, autonomy, meaning, resilience, and personal development.

Historical overview. The main milestones in the development of the concept of well-being are summarised in Table 1. The most recent stages, digital well-being and well-being in AI-mediated environments, provide the direct context for the present review.

In the digital era, the concept has been extended to digital well-being, which concerns how people can benefit from digital technologies while limiting the associated risks [2]. The growing role of AI systems adds a further dimension, as well-being is now shaped not only by human-to-human interaction online but also by interaction with intelligent systems [4].

Table 1. Milestones in the conceptual development of well-being

Period	Milestone
Antiquity	Aristotle's concept of <i>eudaimonia</i>
1946	WHO Constitution defines health as complete physical, mental, and social well-being
1969	Bradburn [9]: the structure of psychological well-being
1984	Diener [6]: subjective well-being
1989	Ryff [7]: multidimensional psychological well-being
2002	Keyes [8]: the mental-health continuum
2000s–2020s	Emergence of research on digital well-being
Present	Well-being in AI-mediated environments

Source: compiled by the authors

Theoretical Frameworks in Cyberpsychology

Cyberpsychology draws on several complementary theoretical traditions to explain why the psychological consequences of technology use vary substantially across individuals. Early media-effects research was strongly influenced by Uses and Gratifications Theory, which reconceptualised media audiences as active agents who selectively engage with media to satisfy specific psychological and social needs, such as information acquisition, entertainment, identity development, and interpersonal connection [10]. This perspective remains influential because it emphasises that the same technological platform may serve different functions for different users and, consequently, produce different psychological outcomes.

A complementary perspective is provided by the Differential Susceptibility to Media Effects Model (DSMM), which proposes that media effects are not uniform but vary according to users' dispositional, developmental, and social-contextual characteristics [11]. Individual characteristics influence both media selection and responses to media experiences, which helps explain why the same digital activity may produce positive outcomes for some individuals and negative outcomes

for others. Media effects are also conceptualised as dynamic and reciprocal: psychological states influence technology use, and technology use influences psychological well-being over time [11].

Together, the two models have three practical implications for research. First, outcomes should be studied at the level of specific activities rather than total exposure. Second, individual and contextual moderators should be measured and modelled explicitly. Third, because effects may be reciprocal, longitudinal designs are needed to establish the direction of influence. These implications guide both the conceptual model proposed below and the evaluation of evidence in the section Evidence on IT- Related Factors and Well-Being.

Contemporary research increasingly recognises the importance of understanding not only whether technology is used, but also how it is used, by whom, for what purpose, and within which social and psychological context [1], [2]. Individual and environmental characteristics shape digital behaviours and experiences, and these relationships may change over time. The World Health Organization (WHO) Regional Office for Europe [2] accordingly describes the relationship between digital technology use and mental health as bidirectional and context-dependent.

For example, engagement in learning activities, digital work, or meaningful interpersonal communication differs qualitatively from passive consumption of algorithmically recommended content, even when the time spent using technology is comparable. This distinction has contributed to a shift from simple measures of overall technology exposure towards multidimensional models of digital behaviour that incorporate the nature and context of technology use [1], [2].

Building on these considerations, the review first conceptualises the relationship between digital behaviour and psychological well-being at a general level:

$$PWB = f(T, U, C, I, E), \quad (5)$$

where: *PWB* is psychological well-being; *T* is type of technology used; *U* is intensity and pattern of technology use; *C* is context of technology use; *I* is individual characteristics; and *E* is social and environmental conditions.

Each component of the model captures a different source of variation. *T* distinguishes, for example, social media from gaming or AI systems; *U* captures not only how much but also when and how regularly technology is used; and *C* reflects the setting of use, such as work, education, leisure, or social interaction. The individual (*I*) and environmental (*E*) components include factors such as age, gender, personality, pre-existing mental health, social support, and socioeconomic conditions.

This formulation is proposed as a conceptual framework rather than an established mathematical model. Its multidimensional structure reflects evidence that associations between technology use and psychological well-being vary according to individual characteristics, contextual influences, patterns of use, and the nature of digital experiences [1], [2]. Consistent with the DSMM, individual characteristics (*I*) and social and environmental conditions (*E*) may moderate both the strength and the direction of these relationships [11].

An important distinction in this literature is between intensive and problematic technology use. High-frequency engagement should not automatically be interpreted as problematic behaviour, because the psychological implications of technology use depend on its characteristics, motivations, and consequences [1]. Evidence reviewed by the WHO similarly indicates that some digital activities can generate positive and negative outcomes at the same time, and that relationships between technology use and mental health are often reciprocal rather than unidirectional [2].

The emergence of AI and increasingly personalised digital systems further increases the relevance of this research. As AI systems are adopted across diverse domains, human interaction with AI has become an important area of investigation within human–computer interaction research. Human-centred AI scholarship emphasises the importance of balancing system autonomy with meaningful user agency and involvement in the design and operation of AI systems [4].

An important scientific challenge is therefore to identify, operationalise, and quantify the relationships between specific technology-related factors and psychological well-being. Existing

literature supports considering multiple dimensions of digital experience rather than relying on a single measure of technology exposure [1], [12].

Accordingly, the general model above can be operationalised as a multidimensional factor model, in which each component of digital behaviour is represented by a measurable variable:

$$PWB = f(ST, SM, SP, IO, OSS, DG, RW, AI, SD, NOE | X), \quad (6)$$

where: *ST* is screen time and type of screen-based activity; *SM* is social media behaviour; *SP* is smartphone usage patterns; *IO* is information overload; *OSS* is online social support; *DG* is digital gaming; *RW* is remote work; *AI* is interaction with AI systems; *SD* is technology-related sleep disruption; *NOE* is cyberbullying and other negative online experiences; and *X* is individual, social, and environmental characteristics. *X* corresponds to the individual and environmental components (*I* and *E*) of the general model, while the remaining variables specify the type, pattern, and context of use (*T*, *U*, and *C*). Consistent with the DSMM, *X* is expected to moderate both the strength and the direction of each association.

The proposed variables should not be assumed to exert equivalent or causal effects on psychological well-being. Their relevance and relative importance should instead be established through literature review, validated measurement instruments, exploratory analyses, and empirical testing. Taken together, these theoretical perspectives show that cyberpsychological research has moved beyond asking whether technology affects well-being in a uniform direction, towards identifying the mechanisms through which different forms of digital engagement influence psychological outcomes, for whom these effects occur, and under which conditions they emerge.

Evidence on IT-Related Factors and Well-Being

Analytic approaches and the specification-curve debate. Much of the debate concerns not the data but the choices made in analysing them. Orben and Przybylski [12] applied specification-curve analysis (SCA) to three large adolescent datasets, estimating thousands of plausible model specifications. They concluded that digital technology use explained at most about 0.4% of the variance in adolescent well-being, an association comparable to everyday behaviours such as eating potatoes.

Semken and Rossell [13] challenged this conclusion, arguing that SCA used for inference can produce biases and false positives through inappropriate covariate adjustment, and can mask heterogeneity in effects. Their Bayesian Specification Curve Analysis (BSCA), which uses Bayesian Model Averaging to model heterogeneous effects across treatments, outcomes, and sub-populations, found that well-being was negatively associated with electronic device use. It also found that social media use was negatively associated with self-assessed but positively associated with parent-assessed well-being, and that the negative association with self-assessed well-being was stronger for girls. These effects, they argued, are hidden when only median estimates are reported.

The debate shows that the size and even the direction of associations can depend on modelling decisions. This supports multilevel and moderated models that estimate effects separately for different behaviours, outcomes, and groups.

Screen time and smartphone use. Overall screen time shows small aggregate associations with well-being [12], but these averages conceal variation by device, activity, gender, and informant [13]. For smartphones, the key distinction is between intensive and problematic use. Problematic smartphone use, characterised by loss of control and functional impairment, is consistently associated with depressed mood, anxiety, stress, and poor sleep quality [14].

Social media use. Social media is the most extensively studied factor, yet conclusions remain divided. An umbrella review by Valkenburg, Meier, and Beyens [3] found that reviews of largely the same evidence reach different conclusions, depending partly on how authors interpret small effects and which designs they include. SCA-based work points the same way: associations can reverse depending on whether teenagers or parents report well-being [13].

Information overload. Information overload occurs when the volume of incoming information exceeds a person's capacity to process it. The problem has been intensified by the digitalisation of work, and it is linked to employee health, well-being, and performance [15]. However, the construct is measured inconsistently, from single items to multidimensional scales, and much of the evidence comes from occupational settings. Both factors limit synthesis and comparison across studies.

Online social support. Digital communication can provide emotional and informational support, which is particularly valuable for people who are geographically isolated, belong to marginalised groups, or have limited face-to-face contact. Social media can offer adolescents opportunities for social connection, identity development, and social support [16]. A meta-analysis of 14 studies with 11,616 adolescents found that online social support was moderately associated with higher self-esteem ($r = .29$) but showed only a small, non-significant association with depression ($r = -.09$). Support from real-life acquaintances also appeared more beneficial than support from people known only online [17]. Online social support may therefore protect some aspects of well-being, although longitudinal studies are needed to establish causality.

Digital gaming. Vuorre et al. [18] linked six weeks of objective game-behaviour data from 38,935 players, provided by seven game publishers, with three waves of self-reported well-being. They found little to no evidence for a causal connection between playing time and well-being. Motivation, however, mattered: intrinsic motivation was positively, and extrinsic motivation negatively, related to well-being. For gaming, why people play appears to matter more than how long they play.

Remote work. The effects of remote work on mental health are mixed. In a rapid review, Oakman et al. [19] found that health outcomes depended strongly on organisational and colleague support, social connectedness outside work, and work–family conflict, and that women were less likely to experience improved health outcomes when working at home. A later systematic review of 64 articles similarly described working from home as dualistic in nature [20]: it can offer autonomy and flexibility, but it can also increase isolation and blur work–life boundaries.

Interaction with AI systems. Experimental evidence on AI and well-being largely concerns conversational agents designed for mental health support. In a meta-analysis of 15 randomised controlled trials, Li et al. [21] found that such agents significantly reduced symptoms of depression (Hedges' $g = 0.64$) and distress ($g = 0.70$), but did not significantly improve overall psychological well-being ($g = 0.32$, 95% CI -0.13 to 0.78). These findings concern purpose-built interventions and cannot be generalised to everyday use of general-purpose AI. For everyday use, questions of trust, autonomy, and cognitive dependence remain largely unexamined [4].

Cyberbullying and negative online experiences. Cyberbullying shows some of the most consistent negative associations in the field. A meta-analysis of adolescent samples reported correlations between cybervictimisation and anxiety ($r = .31$) and depression ($r = .28$), with the percentage of female participants and continent acting as moderators [22]. These effects are considerably larger than those typically found for screen time. The relationship may also be reciprocal, since anxiety and depression can predict later cybervictimisation.

Technology-related sleep disturbance. Hale and Guan [23] reviewed 67 studies and found that screen time was adversely associated with sleep outcomes, mainly shorter duration and delayed timing, in 90% of them. They also noted important limitations: causality was not established, and exposure and sleep were measured with error. Because sleep is closely linked to mood and cognition, sleep disruption may be one pathway through which technology use affects well-being more broadly.

Summary of the evidence. Broad exposure measures, such as overall screen time, social media time, and gaming time, show small and inconsistent associations with well-being. Specific experiences and mechanisms show stronger and more consistent ones: cyberbullying, sleep disruption, problematic use, and motivation. For several factors (social media, remote work, AI interaction), the direction of the association depends on the user, the context, and how well-being is measured. These findings motivate the move from population-average estimates towards the

personalised, causal approach set out in the section Mathematical Models and Intelligent Decision-Support Systems.

Mathematical Models and Intelligent Decision-Support Systems

Because the average association between technology use and well-being is small [12] but varies considerably between individuals [1], it is more useful to model combinations of digital behaviours and personal characteristics than to treat technology as simply good or bad. For an individual i :

$$PWB_i = f(X_i, D_i) + \varepsilon_i \quad (7)$$

where, X_i denotes individual and contextual characteristics, D_i modifiable digital behaviours, and ε_i unobserved influences. Heterogeneous effects can be captured with interaction terms or multilevel models.

A model that predicts well does not, however, establish cause and effect. Most studies are observational, and the relationship may run in both directions [2]. A purely predictive model could therefore recommend changes based on non-causal associations.

The recommendation problem should instead be defined in terms of what would happen if a person changed their behaviour:

$$D_i^* = \arg \max_{D_i \in \mathcal{D}_i} \{E[PWB_i | do(D_i), X_i] - \lambda \|D_i - D_i^0\|\}, \quad (8)$$

where the *do*-operator [24] denotes the expected well-being if the behaviour were actively changed, rather than the well-being observed among people who already behave that way. D_i^* is the recommended behaviour profile. $\mathcal{D}_i$ is the set of realistic options, since some technology use is necessary for work, study, and social contact. D_i^0 is current behaviour, and the penalty term, weighted by $\lambda \geq 0$, favours small, achievable changes. Recommendations should also account for uncertainty and prefer changes whose benefit is clearly supported by data.

Estimating such effects requires longitudinal designs, randomised interventions, or appropriate causal-inference methods. Predictive modelling is thus only a first stage, and recommendations can be trusted only once their effects have been causally tested. The aim is not simply to reduce technology use: WHO stresses reducing digital risks while retaining the benefits of digital environments [2], and social media can support social connection, learning, and identity development [16]. Such systems also raise ethical issues, including privacy, consent, the use of data from minors, and the risk of harmful advice when a model is wrong, which must be addressed in their design.

Conclusions and Future Research Directions

This review indicates that the relationship between IT-related factors and psychological well-being is small at the aggregate level, highly heterogeneous across individuals, and shaped by the specific factor examined, the analytic model applied, and the population studied. Screen time and smartphone use show small aggregate effects that mask considerable variation [12], [13]. Social media research remains divided across methodologies [3]. Cyberbullying and sleep disturbance show more consistent negative associations [22], [23], and interaction with AI systems is an emerging factor whose consequences are only beginning to be studied [21]. Online social support, gaming, and remote work show that the same technology can have opposite effects depending on how it is used [17], [18], [19]. Information overload remains difficult to assess because of inconsistent measurement.

Taken together, technology use is most likely to support psychological well-being when it is active rather than passive, intrinsically motivated, socially connecting, and does not displace sleep, and when it takes place in supportive contexts. Risks are concentrated in problematic use, negative online experiences such as cyberbullying, and night-time use that disrupts sleep [25].

Methodologically, the evidence favours approaches that model heterogeneity explicitly. Multilevel, moderated, and Bayesian specification-curve models give a more accurate account than

single population-average estimates, which can mask associations of opposite direction [13]. Building on this, the review proposes a causal framework for personalised decision support based on the expected effect of changing an individual's behaviour, $E[PWB | do(D), X]$, rather than on population correlations. Its practical value depends on causal estimates that current, largely cross-sectional evidence cannot yet provide, and ethical safeguards must be built into such systems from the outset.

Future research should prioritise longitudinal and experience-sampling designs to separate within-person change from between-person differences. It should also develop more consistent measures of IT-related factors, particularly information overload and AI interaction. Finally, reviews should report how sensitive effect sizes are to reasonable alternative modelling choices, so that policy recommendations rest on the most robust, rather than the most convenient, statistical account of the evidence.

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Використання цифрових технологій та психологічного благополуччя: огляд доказових даних і каузальна модель для персоналізованої підтримки прийняття рішень

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АНОТАЦІЯ

Цифрові інформаційні технології глибоко інтегрувалися в повсякденне життя, змінивши комунікацію, освіту, роботу та соціальну взаємодію й породивши нагальні питання щодо їхніх психологічних наслідків. У цьому огляді узагальнено сучасні дані про вимірювані ІТ-чинники (екранний час, використання соціальних мереж, використання смартфонів, інформаційне перевантаження, онлайн-соціальна підтримка, цифрові ігри, дистанційна робота, взаємодія зі штучним інтелектом, кібербулінг і порушення сну, пов'язані з технологіями) та їхні зв'язки з психологічним благополуччям і психічним здоров'ям. Також розглянуто статистичні підходи до кількісної оцінки цих зв'язків, зокрема аналіз кривої специфікацій і багаторівневе моделювання. Дані свідчать, що зв'язки між загальним використанням технологій і благополуччям є слабкими на агрегованому рівні та дуже неоднорідними залежно від особи й контексту, тоді як кібербулінг і порушення сну демонструють послідовніші негативні зв'язки. На основі цих результатів запропоновано каузальну модель персоналізованої підтримки прийняття рішень, у якій рекомендації ґрунтуються на очікуваному ефекті реальної зміни цифрової поведінки людини, а не на спостережуваних кореляціях, і надають перевагу невеликим, досяжним змінам, що зберігають переваги використання технологій. Зроблено висновок, що для подальшого прогресу потрібні лонгitudні та експериментальні дослідження, а також дослідження з використанням методу вибірки досвіду (experience sampling), послідовніше вимірювання ІТ-чинників і звітування про чутливість результатів до вибору методів моделювання.

Ключові слова: психологічне благополуччя; психічне здоров'я; кіберпсихологія; соціальні мережі; штучний інтелект; каузальне моделювання; персоналізована підтримка прийняття рішень

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