Environment and Social Psychology (2026) Volume 11 Issue 3 ISSN: 2424-8975 (O)
doi: 10.59429/esp.v11i3.4549 2424-7979 (P)

RESEARCH ARTICLE

From behavioral dependence to economic cost: Reframing digital addiction in economic terms

Constantinos Challoumis[1,2,3,*], Nikolaos Eriotis[2], Dimitrios Vasiliou[2]

[1] *Department of Accounting and Finance, Faculty of Business, Philips University Nicosia P.O.Box 28008, 2090 Strovolos, Cyprus*

[2] *Department of Business Administration, School of Economics and Political Sciences, National and Kapodistrian University of Athens, Sofokleous str. 10559 Athens, Greece*

[3] *Department of Marketing and Communication, Athens University of Economics and Business, 76 Patission Str. GR-10434 Athens, Greece*

*** Corresponding author:** Constantinos Challoumis, conchall@uoa.gr or conchall@aueb.gr; challoumis_constantinos@philipsuni.ac.cy

ABSTRACT

Digital addiction is typically examined as a psychological or behavioral condition, while its broader economic consequences remain insufficiently addressed. This paper reframes digital addiction as an economic pathology, emphasizing its welfare and productivity implications across individuals, organizations, and public systems. Drawing on behavioral economics, time-allocation theory, and the economics of externalities, the study develops a theory-driven analytical framework to map the diffusion of economic costs associated with excessive digital use. Methodologically, a structured literature synthesis is combined with relative intensity scoring and heatmap visualization to compare cost channels and affected stakeholders. The findings indicate that the primary economic burden arises from time misallocation, productivity losses, and social spillovers rather than direct expenditures alone, with costs distributed asymmetrically across the economy. The framework provides a diagnostic basis for future empirical research and policy intervention in the digital economy.

Keywords: digital addiction; behavioral dependence; welfare economics; economic externalities; time allocation; productivity loss; opportunity cost; digital platforms; public policy

1. Introduction

Digital or internet addiction remains a controversial topic across a range of academic disciplines, including psychology, sociology, and medicine. Expanding the analysis into economics offers an alternative perspective, subsequently clarifying terminology and applying economic testable implications as well. The perspective taken here draws on behavioral economics, integrating concepts of time incompatibility, behavioral dependence, and distorted differential discounting. By considering moderation from a public health perspective, the approach replicates the logic employed in public-health-based examinations of

ARTICLE INFO
Received: 14 January 2026 | Accepted: 28 January 2026 | Available online: 6 March 2026

CITATION
Challoumis C, Eriotis N, Vasiliou D. From behavioral dependence to economic cost: Reframing digital addiction in economic terms. *Environment and Social Psychology* 2026; 11(3): 4549 doi:10.59429/esp.v11i3.4549

smoking. The objective is to explore digital addiction (the term behavioral dependence is used as an economic construct distinct from clinical addiction, referring to welfare-reducing overconsumption driven by self-control distortions) from a behavioral-dependence perspective drawn from the psychology literature and translate its usefulness into widely accepted economic arguments. These behavioral-dependence digital arguments are then synthesized by applying standard economic theory to formalize digital use as an activity that produces a utility stream over time. Controlling the function parameters allows one simultaneously to capture both the usual consumer-surplus-based positive use and the behavioral-dependence negative use—all within a single model[1-3–10,11–19]. At this point, testing the behavioral-dependence condition requires a simple examination of the effect of income changes on digital-use time, an approach compatible with the usual testing process.

2. Literature review

The present research engages literature selectively and interpretively rather than cumulatively. Empirical contributions documenting associations between excessive digital use, delay discounting, compulsive behavior, and productivity impairment provide the evidentiary foundation demonstrating that digital overuse generates measurable behavioral distortions. These studies substantiate the claim that digital addiction is not merely a descriptive psychological category but a phenomenon with observable welfare implications. Complementing this empirical base, conceptual contributions from welfare economics, consumer theory, and the economics of externalities supply the formal tools required to reinterpret behavioral dependence as a source of social cost. In particular, research on consumer surplus measurement, non-market valuation, and digital goods clarifies how time misallocation and attention extraction alter effective utility and reduce net welfare, while externality theory explains how private digital consumption propagates costs across households, firms, and public systems. By explicitly distinguishing between empirical validation and theoretical interpretation, the paper integrates behavioral evidence with established economic frameworks, thereby positioning digital addiction as an economic pathology characterized by systemic inefficiencies rather than as an isolated behavioral anomaly.

Digital addiction has received considerable academic and public attention, prompting interest beyond traditional medical fields to psychology, media studies, marketing, and economics. However, these discussions remain largely in psychological terms of behavioral dependence and compulsive use. By contrast, economic theory emphasizes the welfare cost of products that negatively affect health or productivity and supplies a microfoundation for quantifying and predicting external costs. Nevertheless, this perspective has not yet been applied to digital use. Overlooked in the empirical literature is the economic viewpoint—the behavioral- or health-dependence construct is not established as a digital addiction concept—and guiding questions remain unanswered. Discussions on addiction and risk encompass both problems and applications. Behavioral dependence is defined in Section 2.1, highlighting contrasts with other forms of dependence, practical measurement particularities, and specific empirical validation. Building on relevant economic theory—externality concepts and related constructs from welfare economics and consumer theory—Section 2.2 interrogates how a form of consumer surplus or economic value can be associated with digital addiction. Direct costs, productivity losses, and social externalities constitute the three main types of effects considered[20–29].

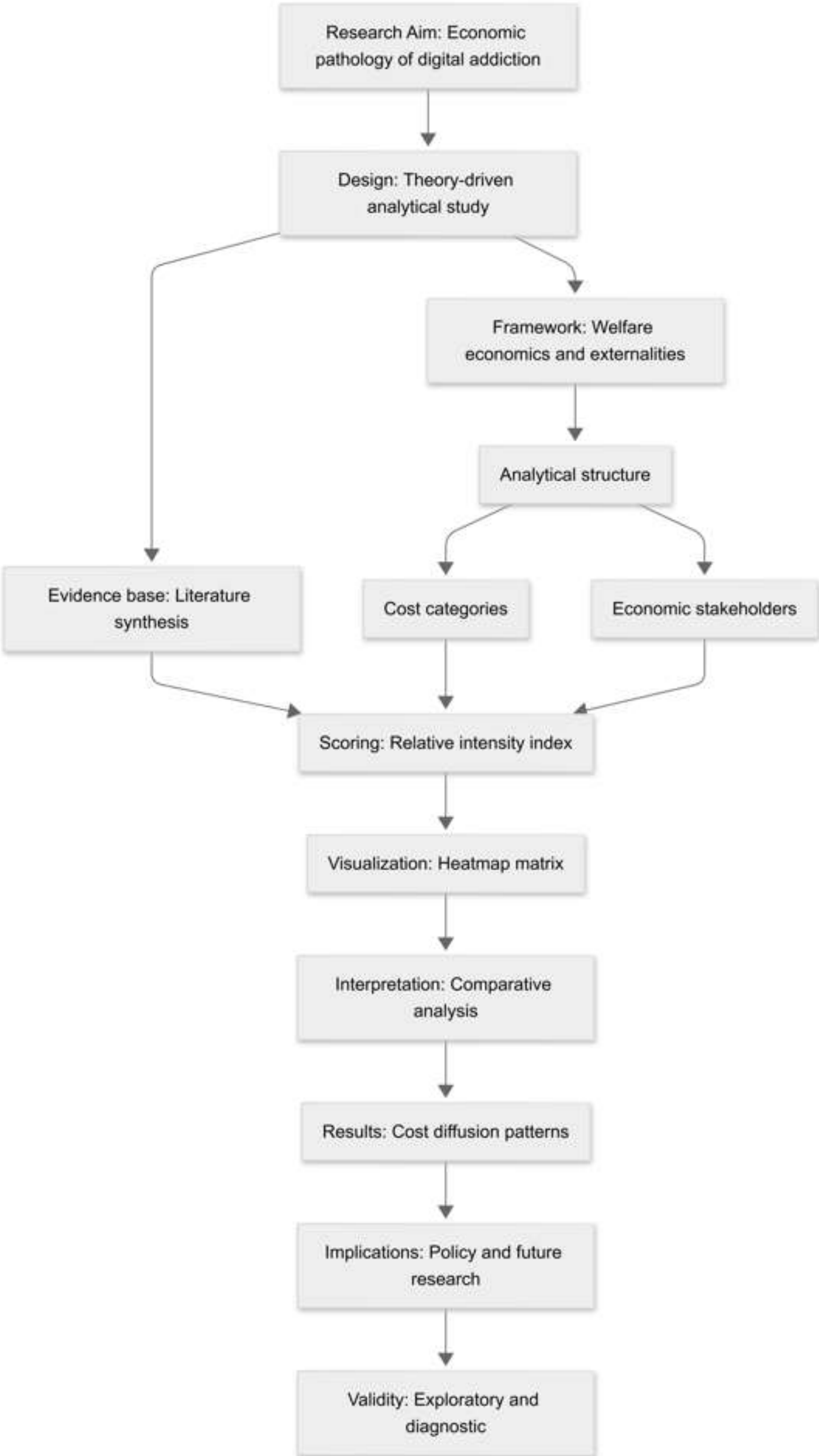

Figure 1. Behavioral dependence to economic cost (Authors' scheme).

Figure 1 presents the methodological framework of the study, outlining the sequential and integrative process through which digital addiction is analyzed as an economic pathology. The framework begins with the formulation of the research aim, which positions digital addiction as a systemic economic phenomenon rather than a purely individual or clinical condition. This aim informs the adoption of a theory-driven analytical design, emphasizing conceptual rigor and structural interpretation [30,31]. The framework then specifies the theoretical foundation of the analysis, grounded in welfare economics and the theory of externalities. Within this framework, an analytical structure is developed that distinguishes between two core dimensions: economic cost categories and affected economic stakeholders. These dimensions capture both the types of costs generated by digital addiction and the agents across whom these costs are distributed, enabling a multidimensional representation of economic impact. Empirical grounding is provided through structured literature synthesis, which informs the identification and weighting of relevant cost channels and stakeholders. Insights from this synthesis are integrated into a scoring procedure based on a relative intensity index. This index standardizes the perceived magnitude of economic burden across dimensions, allowing for systematic comparison without reliance on direct monetary measurement. The scored matrix is subsequently translated into a heatmap visualization, which serves as the primary analytical tool of the study. The heatmap facilitates comparative analysis by visually highlighting cost concentrations, asymmetries, and diffusion patterns across the economic system. Interpretation of the results focuses on relative intensities rather than causal inference, emphasizing structural relationships and transmission mechanisms. The final stages of the framework synthesize these findings into identifiable patterns of cost diffusion, which inform broader policy implications and directions for future research. The methodological approach concludes by explicitly acknowledging its exploratory and diagnostic character, positioning the framework as a foundation for subsequent empirical validation and policy-oriented investigation.

A systematic content analysis of the reviewed literature was performed to ensure that the heatmap visualization reflected systematic analysis and not illustrative or hypothetical values. This procedure aimed to convert qualitative and quantitative findings from the literature corpus into a reproducible relative intensity matrix capturing how documented economic costs are distributed across different stakeholder groups. Therefore, the heatmap reflects results derived from applying a defined coding protocol to the reviewed studies rather than relying on demonstrative values. The unit of analysis was each individual peer-reviewed study that comprised the final literature corpus. Each study was assessed for whether it provided identifiable evidence for a particular category of economic cost and a clearly attributable stakeholder group affected by that cost. Studies discussing digital overuse or behavioral dependence without explicit economic implications were retained in the conceptual review but excluded from the quantitative scoring procedure. Only studies identifying measurable or analytically inferable economic consequences were included in calculating intensity. Each eligible study was coded according to three structured dimensions. First, one or more predefined cost categories were assigned to the research—for example, productivity loss, healthcare burden, educational disruption, household welfare loss, regulatory cost, and macroeconomic distortion. Assignment required an explicit textual, empirical, or modeled linkage between digital overuse and the stated economic outcome. Second, attribution of identified economic burden was made to a relevant stakeholder group—individuals, households employers public institutions digital platforms or wider macroeconomic system—with attribution requiring either direct incidence or clearly inferable transmission mechanism supported by study's analysis. To limit subjective interpretation, a weighted scoring framework was used whereby each study received an evidence weight based on methodological rigor and an economic linkage weight based on strength of documented cost channel. Evidence weights were assigned as follows: causal empirical designs using instrumental variables, panel identification, or quasi-experimental approaches received the highest weight; quantitative empirical analyses using regression or statistical estimation received the next highest weight; formal theoretical economic models received moderate weight; purely conceptual or qualitative analytical discussions received the lowest weight. Economic linkage weights were assigned based on whether a study reported direct quantified economic cost, demonstrated indirect but analytically supported economic implication, or proposed conceptual or hypothesized economic pathway without quantification. For each cost–stakeholder cell in the matrix, a raw score was computed as the sum of the products of evidence weight and linkage weight across all studies assigned to that cell. This aggregation procedure ensured that both methodological rigor and economic specificity contributed proportionally to the final intensity measure. The resulting raw scores were normalized to a 0–10 scale to allow comparability across categories. The normalized index thus represents relative structural salience within the literature corpus rather than monetary magnitude or aggregate macroeconomic cost. All coded observations, study identifiers, assigned categories, applied weights, and computed contributions to each matrix cell are provided in Supplementary File S1 for transparency and reproducibility. The heatmap in the results section is generated directly from this aggregated scoring matrix created with Python-based data processing and visualization tools. Therefore, it reflects the systematic content analysis described above and does not rely on illustrative or placeholder data.

2.1. Behavioral dependence in digital contexts

Much of the academic literature uses measures or proxies of behavioral dependence. This approach has advantages and drawbacks. The principal benefit is that behavioral dependence captures a multifaceted phenomenon specific to digital environments, typically comprised of obsessive, compulsive, and excess use. However, despite widespread usage, behavioral dependence remains conceptually problematic. First, it lacks clear differentiation from other forms of dependence. Second, its assessment is fraught with practical difficulties, including conceptual ambiguity and issues of scale[32,33,34–41,42–46]. Nonetheless, the various characteristics habitually associated with behavioral dependence — such as indices of compulsive use or the distress that excessive amounts of online time elicits in affected users — have been extensively modelled in economic terms. Recent studies have examined the presence of (non-)social equilibrium conditions in time-allocation processes that incorporate both e-gambling and general use of the internet or social-media platforms, and these two areas of investigation can readily be taken together. Many findings are predicted or implied by standard economic theory, and it is therefore natural to delimit a special section on economic theory for the purposes of this synthesis.

To avoid mixing up ideas and to keep terms clear, this study makes a clear difference between the clinical idea of “digital addiction” and the economic idea of “behavioral dependence.” The term digital addiction comes from clinical psychology and psychiatry. It means compulsive digital use with tolerance, withdrawal symptoms, and functional impairment. This study does not follow clinical diagnostic criteria, but uses the term behavioral dependence as an economic concept that highlights distortions in welfare due to ongoing patterns of digital consumption.

In economics, behavioral dependence means that a person keeps on doing something digitally even when it becomes less enjoyable because they have problems with self-control, rationality within limits, preferences that change over time or reinforcement mechanisms induced by algorithms. Formally speaking behavioral dependence happens when the instant perceived utility from digital consumption is different from what would maximize long run welfare for the individual causing overconsumption compared to some intertemporal optimum. It could create internal welfare losses as well as externalities impacting employers households public institutions and larger economic systems. This definition separates behavioral dependence from clinical addiction in two key ways: First, it does not require pathological classification or medical diagnosis; rather, it identifies a welfare-relevant behavioral distortion observable through economic outcomes such as productivity loss, opportunity cost misallocation, or increased healthcare burden. Second, it allows for a continuum of intensity rather than a binary addicted/non-addicted state. Behavioral dependence therefore functions as an economic mechanism explaining resource misallocation and external cost generation while digital addiction remains a clinical diagnostic category grounded in psychiatric assessment. The term digital addiction is used only for reference to literature in clinical and psychological research; all other instances will be based on the operational definition above. This distinction ensures conceptual clarity and prevents conflation of medical diagnosis with economic welfare analysis.

2.2. Economic theory and externalities

Harmful behavioral dependence constitutes a negative externality of digital use, linked to concepts such as consumer surplus and social welfare in welfare economics. Externalities arise when the consumption of goods and services affects parties not directly involved in the transaction. A negative externality occurs when the consumption of a good by one agent reduces the welfare or utility of another; examples include air pollution from a factory or noise generated by a nightclub. When the social cost of a good exceeds its private cost, society derives greater welfare from consuming less of it; if the social value of a good exceeds its private value, society maximizes welfare by consuming more. Real-life situations rarely fall into these clear-cut categories, yet they provide a useful starting point for analysis. Consumer surplus is the difference between what a consumer is willing to pay and the actual price paid. Social welfare is maximized when the sum of consumer surplus is greatest. Digital use generates benefits for society, but behavioral dependence also causes losses to individuals and, indirectly, to families, friends, associates, employers, and public services. As a consequence, the costs of dependence reduce the net benefits of digital use and represent a social externality. These costs must therefore be considered in assessing the overall economic value of digital demand. Externalities can also be viewed as spillovers, expressed in nonmonetary terms, positive or negative, experienced by consumers, producers, or other parties not directly engaged in the transaction. In this sense, behavioral dependence constitutes a negative spillover associated with the use of digital products and services. Consumer surplus, social welfare, negative externalities, and spillovers are thus closely related concepts that help assess the overall value of a digital market[47–53].

3. Methodology

A theoretical literature review is conducted to examine behavioral dependence in digital use and its associated economic costs of behavioral dependence in digital environments. The selection of economic literature on these costs is guided by cross-arts conceptual maps that connect these constructs with key economic aspects or principles. Although of economic origin, much behavioral-economics literature discusses behavioral dependence in digital contexts. Most studies model time allocated to digital media as a dependence-like behavior, applying premises from habit-formation theory—recognition of diminished preference for a digital medium, even concurrently—inconsistent intertemporal choice, and failure of self-control or preference change. Construct validation has yielded positive associations with existing dependence scales. These digital-are-of-assets consumptions-related costs and consequences, although formulated in behavioral terms, would be logically connected to the concept of externality. Here, behavioral dependence is distinct from addiction, including a compulsive-use threshold. Cross-arts analyses attempt to capture such a pattern.

Table 1. Structure of the methodological design (authors' table).

Methodological Component	Description	Output / Analytical Role
Research Design	Theory-driven conceptual framework reframing digital addiction as an economic pathology rather than solely a behavioral condition.	Establishes analytical lens grounded in welfare economics and externality theory.
Literature Synthesis	Structured and selective review of empirical and theoretical literature across behavioral economics, welfare economics, and digital market studies.	Identifies cost channels, theoretical mechanisms, and stakeholder transmission pathways.

Methodological Component	Description	Output / Analytical Role
Conceptual Classification	Mapping of literature into seven cost categories and five stakeholder groups.	Creates analytical matrix structure (cost × stakeholder dimensions).
Scoring Procedure	Relative-intensity index (0–10 scale) assigned using qualitative-to-quantitative translation rule based on literature density and theoretical centrality.	Produces standardized comparative matrix reflecting structural salience (not monetary magnitude).
Normalization	Scores harmonized across categories to ensure comparability and interpretive consistency.	Enables cross-dimensional comparison without econometric estimation.
Visualization	Heatmap constructed using Python (NumPy, Pandas, Matplotlib).	Visual diagnostic tool highlighting cost concentration and asymmetry.
Interpretation	Structural analysis of diffusion patterns, asymmetries, and stakeholder burden distribution.	Identifies systemic inefficiencies and policy leverage points.
Policy Translation	Integration of results with cost–benefit logic and behavioral public economics.	Generates policy-relevant implications and research extensions.

Table 1. (*Continued*)

Table 1 shows the sequential architecture of the methodological framework employed in this study, clarifying how conceptual reasoning is translated into structured analytical output. The first component, Research Design, establishes the theoretical foundation by positioning digital addiction as an economic pathology within the analytical boundaries of welfare economics and externality theory. This step defines the epistemological orientation of the study and frames the inquiry beyond purely behavioral or clinical interpretations. The second stage, Literature Synthesis, involves a structured and selective integration of empirical and conceptual research from behavioral economics, welfare analysis, and digital market studies. Rather than accumulating references descriptively, the synthesis identifies relevant mechanisms through which digital overuse generates welfare distortions, productivity losses, and spillovers. Through Conceptual Classification, these insights are systematically organized into seven cost categories and five stakeholder groups. This classification creates a multidimensional analytical matrix that operationalizes the diffusion of economic costs across economic agents. The Scoring Procedure introduces a relative-intensity index on a standardized 0–10 scale. Scores are assigned through a qualitative-to-quantitative translation rule reflecting literature density, theoretical centrality, and inferred transmission strength. This step transforms conceptual interpretation into a structured comparative framework without implying monetary valuation or econometric precision. Normalization ensures cross-category comparability by harmonizing intensity values, allowing structural comparison across dimensions without statistical inference. The Visualization stage translates the standardized matrix into a heatmap using Python-based computational tools. The purpose of the visualization is diagnostic rather than inferential, enabling immediate identification of concentration effects and asymmetries. Subsequently, Interpretation focuses on structural diffusion patterns and stakeholder burden allocation, highlighting systemic inefficiencies generated by behavioral distortions in digital environments. Policy Translation integrates the analytical findings into cost–benefit reasoning and behavioral public economics, deriving implications for regulation, taxation, platform design, and public health interventions. **Table 1** demonstrates that the methodology follows a coherent progression from theoretical framing to structured synthesis, standardized scoring, visual diagnostics, and policy-oriented interpretation, thereby ensuring internal consistency, transparency, and replicability within the defined exploratory scope.

4. Measurement and valuation

Digital addiction constitutes an economy-wide externality affecting consumer welfare and social productivity. Valuing digital addiction entails estimating its direct costs, opportunity costs, and societal spillovers. Individuals incur direct costs from digital-use dependencies, including increased healthcare expenditures, diminished non-market leisure time, and deadweight losses in the value of lost attention. For health expenditures, a general measure of addiction-specific costs is the alcohol consumption—a leading contributor to indirect morbidity and mortality, which other substance-use harms support—and for time use, applying Becker's work-leisure equilibrium condition. Total healthcare costs attributable to alcohol in the United Kingdom are available from the Office for National Statistics, as are equivalents for attention-deficit hyperactivity disorder and gambling in Finland. Time traded away from family or partner leisure can be valued in terms of average wage; the cost of reduced time spent on leisure other than spending time with family or partner is bounded by the average wage[54,55]. The resulting values are in £2007 and drawn from Becker et al.'s analysis of the demand for hours of work. Estimates can also be derived for the quantity of addict and non-addict hours for each metropolitan area and sub-group, along with average hourly wages. The foregone productive output corresponding to digital-use dependencies is equal to the total number of time units lost in work diminished by the productivity of the concubines who provided leisure services to the users[56–62].

4.1. Direct costs to individuals and households

The direct costs of behavioral dependence on digital devices borne by individuals and households will consist of health expenditures, money and time spent on digital devices and their substitutes, and the utility losses associated with a diminished quality of free time. Expenditures can usually be retrieved from national health accounts, which break down government and private health spending by function and type. Private health expenditures due to behavioral dependence on digital devices generally take three forms: preventive care, diagnosis and treatment of actual cases, and indirect costs through the care of relatives. The time cost of being in a digital environment is equal to the total user time multiplied by the market wage. Besides the loss of productive time, time spent online tends to trade off with less rewarding leisure activities, which are likely to be considered inferior, and hence to have lower presented prices with respect to working time because of the lower market value. Finally, the welfare losses associated with a diminished quality of free time have received considerably less attention. The means through which behavioral dependence alters the quality of time use outside the digital environment are similar to those identified in the literature surrounding compulsive use: adverse effects on bonds with family and friends, reduction in time spent engaging in meaningful activities that foster happiness, and decrease in the time invested in physical activity, among others. Studies that endogenize user preferences toward free-time attributes, such as quality or richness, and positively examine the impacts of behavioral dependence on the quality of free time will provide the first necessary step toward assessing the economic costs of these losses. Indicators of direct utility losses can be indirectly derived from people's willingness to pay for a better quality of free time[40,41,50,58–64,65–67].

4.2. Opportunity costs and productivity

One important source of economic cost associated with digital activities relates to opportunity costs arising from alternative uses of time. Operating on the presumption that participating in digital activities is not necessarily socially bad, economists decompose the economic cost of digital activities into those costs incurred by consumers and those external costs. The former include the direct costs borne by individuals and households when using digital services, that is, the costs associated with the services that require out-of-pocket expenditures and the opportunity costs associated with spending their time in activities that are more productive than consuming those services. Quantifying those opportunity costs has been challenging, as it requires estimating (1) the amount of time that individuals spend on these activities, (2) how that time could otherwise have been spent and, when valued at the implicit market price of labor, (3) how those services would have contributed to output and national product. A major consideration here relates to the fact that time devoted to digital activities while in traditional employment not only reduces time available for family and social activities but also tends to reduce productivity in the workplace, with a significant percentage of employees admitting that they are multitasking. Several methods are now being used to measure the costs related to the opportunity cost of time. These major approaches can be classified into two groups: (1) contingent valuation, whereby time spent on activities is valued at the individual's hourly wage, which is assumed to reflect the value that the market assigns to the hour; and (2) revealed preferences, which infer how much a consumer would be willing to pay for an additional hour of time and then use the value of that time (rather than the market-measured wage rate) to estimate the opportunity cost of time savings [28,29,40–44].

4.3. Social and systemic externalities

Recent studies suggest that extensive digital use is associated with negative externalities affecting people other than the users themselves, typically family members, co-workers, and society at large. Such externalities should be considered in any economic assessment of digital addiction. Externalities can be understood as situations in which the consumption or production decisions of one economic agent affect the utility or production of others within a competitive market system. When externalities are present, the consumer surplus related to the activity cannot be taken as a complete measure of social welfare. Negative externalities reduce social welfare and need to be subtracted from consumer surplus when determining the net social value of an activity The digital platforms, and especially their product designers and engineers, have the ability to influence the nature of the externalities triggered by users' behavior when engaged with their products. A common expectation is that a product that users find engaging could generate positive externalities, as it creates opportunities for connecting, communicating, and sharing ideas with others. However, it has also been shown in the behavioral addiction literature that many digital platforms and products tend to create persistent, possibly excessive, research, presence, and/or use of users. Such behavior may also trigger negative externalities for family members, friends, co-workers, and the community. Measurement indicators might include the following: the perceived impact of users' digital behavior on parents and children relations (e.g., quality of time spent together, abandonment of family time, broken connections with children); the perceived impact of users' digital behavior in workplace environments (e.g., reduction in quality of work information, contribution to team synergy, spirit, and harmony, perceived impairment of interpersonal professional connections); the perceived impact of users' digital behavior in the health sector (e.g., share of the population suffering or giving at least once in their life the so-called "digital addiction" syndrome; trajectory and evolution of medical expenditures related to the diagnosis and treatment of addictions associated with digital); the perceived usefulness of public or private transitional services specially designed for individuals affected by digital devices engagement products[68–77].

5. Economic models of digital addiction

A set of economic models describes two aspects of behavioral dependence on digital technologies: the allocation of time to digital use and the consistency of preference over time; both play a key role in determining whether and for whom digital use becomes addictive. A third model introduces the concept of digital use as a habit-forming activity with short-run pleasurable but long-run negative consequences. All models connect time allocated to digital use to underlying behavioral dependence, although incidence and extent of dependence do not appear in the models themselves. The conclusions of many studies provide testable predictions of interest for researchers examining these or related issues. One model examines the instantaneous intertemporal choices of a representative consumer with impulse-control problems; it determines the consistency of preference when digital-use gratification is higher in the present than at some future date. A second model analyzes how users make intertemporal choices when some activities require self-control to maintain welfare-regaining digital use[78,79]. The findings address recent empirical concerns regarding self-control, consistency of preference in use of digital technologies, and the preference-adjusting roles of partial uncommitment and partial liquidity constraints. The analysis further substantiates the relevance of economics by exploring implications of behavioral-economics concepts tested in experimental, psychology, and neuroscience literature. A third model frames digital addiction as a digitally-mediated activity where the instantaneous utility function is concave and convex in the short and long run, respectively[63–65,67].

5.1. Time allocation and consistency of preference

Formal theory supporting the cost-benefit logic for habits, compulsive use, and dependence is limited and has rarely assessed implications of time allocation in these settings. A reciprocal model helps address these gaps by integrating the literature on time allocation with habit formation and re-examining implications for consistency of preference. The analysis shows that time spent on a good can be inefficiently high or low and that intertemporal preferences are inconsistent when not all consumption constitutively contribute to a pre-commitment. These results further imply that compulsive use, behavioral dependence, and preference-sense conflicts may coexist in equilibrium. Individuals derive utility from the consumption of multiple goods but may dedicate disproportionate time to one of them. Explicitly model time allocation while analyzing habit formation in the context of a two-good setup: an addictive good, which provides more enjoyment the larger its cumulative consumption is, and a neutral good, whose consumption is unrelated to past consumption[80–84].

5.2. Behavioral economics in digital environments

Choice architecture, nudges, default options, and information frictions represent important concepts from behavioral economics that allow designing contexts and conditions in which individuals take their decisions. Integration of theory, experiments, and practice in behavioral economics enables a more systematic treatment of the framework characteristics of digital environments. Certain elements of choice architecture are already embedded in modern digital environments; others can easily be included, given their inherent flexibility; the introduction of virtual nudges, default options or the simplification of information frictions can go a long way in steering individuals towards better decisions from a welfare perspective[85,86]. The net effect of having the digital environment built according to behavioral economics principles is expected to reduce welfare costs related to addiction and compulsive behavior towards the agent services. Always remaining within a behavioral approach, the superimposition of friction cost theory to classical time allocation models opens new avenues for both the characterization of the digital ecosystem and the assessment of the economic costs it generates. As with any other market, directing more attention towards the friction costs involved in the usage of agent services help quantify the total costs for the society and, in particular, how they relate to the affordability of the platforms offering them[6–10,81,84].

5.3. Cost-benefit analyses and policy simulations

Economic models of digital addiction support empirical exploration. Models align time allocation across activities, incorporate habit formation, and integrate direct costs and utility into a single framework. Time allocation models specify traders possessing standard preferences yet neglecting decision-consistency. Players distribute fixed time over non-competing activities, subject to self-control considerations. Time allocation governs consumption in health-related activities. Standard models can also analyze externalities in online settings. Cloud-computing adoption across U.S. public-safety answering points can be modeled using a four-factor reduced-form model. Cost–benefit, ex ante and ex post, and policy-simulation perspectives have been applied. One benefit–cost analysis has covered the use of cloud computing by public safety answering points in the USA, at both state and national levels. A second assessment has examined the occupational impact of mobile telephony across European economies [87,88]. Behavioral-economics concepts tailored to digital environments have been used to assess time inconsistency and cheapig-related topics. Nudges, default options, information frictions, and other factors impeding intertemporal choices have been identified and quantified for measurement; capitalizing on this knowledge allows the estimation of the welfare gains from removing them. The analysis of the impact of social problems related to excessive use on productivity, governmental expenditure, and the provision of health services, whether acting on public finances or on private welfare, enriches the literature on public-health funding and has cascading implications for both externalities and actual government budgets. Simulations of the consequences of differences in the introduction of supportive and avoiding discourses about addictive behaviors generate expected-net-benefit estimates of interventions aimed at controlling the frequency of addictions, as well as shaping their consequent productivity effects[12,80–82].

6. Policy interventions and economic outcomes

The policy recommendations below are derived directly from the three normative challenges, namely paternalism constraints, distributive cost asymmetry, and institutional incentive misalignment. Several types of policy instruments can be applied to address digital addiction, including regulation, public health, taxation, and changes in platform design. Regulatory measures may apply to digital service providers, directly targeting the consumption of addictive services or the design of addictive platforms. Instrument choice involves a trade-off between effectiveness and the likelihood of providing a precise signal to the underlying causes of digital addiction. Public health approaches target behavior patterns rather than specific products. Health campaigns addressing the general population are likely to deliver the largest returns, as reduced prevalence spreads the direct health cost across a wider pool and lowers the social cost of addiction. Regulation and taxation have similar roles in the digital addiction context but require careful implementation. Regulation may take the form of a ban on advertising among minors and other susceptible groups. Taxes are also a viable option, especially when defining the welfare effects of addictive consumption. Following the well-established principles of optimal taxation, taxes should be directed at the goods or services that generate the greatest negative externality for society. Digital services that generate a negative externality should therefore be taxed. At the same time, the expected revenues from this taxation should be estimated, as evidence shows that people respond favourably to visible tax revenues being earmarked for specific services. Nevertheless, moderation, taxation, or regulation of addictive services may also generate a backlash effect, as addicts tend to react negatively to any perceived moderation of their products[9,12,14–19,80,81, 82].

6.1. Regulatory measures and market incentives

Proposed policy measures addressing addiction-related damage to well-being fall primarily into three categories: regulation, taxation, and user compensation. Regulation seeks to reduce excess demand through restrictions on supply or demand. Taxation increases product prices—using the government's capacity to set prices—so that the quantity demanded will fall to a more socially desirable level. A user compensation scheme requires digital platforms with addictive services to pay the government an amount equal to the estimated costs caused to the users by addiction-related problems. Mandatory addiction moderation is the most frequently proposed regulatory measure. The idea is that digital services would be better designed if users were better protected against the risk of addiction. More generally, a regulatory approach assumes that users cannot always make good decisions themselves. An apparent failure is that users are not concerned about addiction, since those who are concerned are actively searching for moderation instruments that would work. A second approach proposes taxes on services with addiction externalities, such as internet gambling. Such taxes may help to reduce gambling addiction and generate additional tax revenues[25,26,27–29,40,80–83,84].

6.2. Public health approaches and economic returns

Public health measures targeting digital addiction have long-term economic benefits. An integrated empirical framework relates costs and decisions to societal outcomes, evaluating these relationships over time to gauge policy effects on productivity and health expenditures. Cost-benefit analysis quantifies financial returns for a range of investments targeting prevalence reduction, providing rigorous insight for digital welfare investments.

Intervention effectiveness can be modeled as an elasticity linking policy action to addiction rates, with behavioral dependence seen as a disease by some. Reviews identify demand for public health responses, and productivity reductions can be incorporated into broader analyses of digital addiction costs. Previous studies specifically calculate public health intervention ROIs using heroin addiction as a parallel. Digital addiction costs have been documented, and algorithms suggest that easily quantifiable costs can provide conservative ROI estimates. Illustrating this framework, selected addiction rates are treated as behavioral elasticities, enabling new findings from previously compiled digital addiction estimates and associated literature[42–46,89].

6.3. Digital platform design and friction costs

The properties of digital platforms, such as their design choices, shape the time spent on these platforms and, consequently, the welfare of users and society as a whole. Two areas are particularly relevant to addiction: the reduction of friction costs and the ability to design platforms that maximize user engagement. Friction costs are the costs incurred when switching between different activities, such as when users move from gaming to chatting. Friction costs impact time allocation because they limit the number of times that users switch from one activity to another. Easy switching between activities leads to shorter addictive cycles, which is important when two of the activities are mutually exclusive (like chatting and working). If platforms are designed to allow users to switch easily between activities, more of the activity cycles in environments with low marginal utility will be at the bottom and will generate higher public costs. Digital advertising platforms, such as Google and Meta, make user engagement a priority, and this raises ethical concerns. When designing engagement habits, firms have the option of maximizing engagement time (time multiplied by the effective cost of time) or social welfare. A digital adoption externality occurs when an increase in the addiction level of one individual has a positive impact on the welfare of others. The advertising business model creates the three features that lead to such an externality: negative literal costing of the consumption good, exploitation of information asymmetries in choice, and formation of habits[22–27,80,82,84]. The products consumed on digital platforms are not actually free. The revenues that keep the supply of digital services free come from advertising displayed on users' screens. A deeper understanding of digital advertising platforms is needed to assess the social costs and benefits of addiction to digital services and their ethical implications.

7. Normative and political-economic implications of behavioral dependence

Three main ethical and political-economic issues arise directly from the unequal distribution of costs as described in this study. Rather than using metaphorical illustration to highlight these challenges, the analysis below grounds them within normative frameworks that are already established and links them with policy consequences. The first challenge is regulatory paternalism that comes into play when behavioral dependence is identified as a source of welfare reduction. If people over-consume digital activity due to self-control distortions or algorithmically induced reinforcement, then intervention may be justified under a soft paternalist framework. Behavioral welfare economics allows for regulation to be justified when revealed preferences are not consistent with long-run welfare. However, such regulation must meet proportionality and autonomy-respect criteria; hence the ethical dilemma between protecting individuals from self-harm and preserving informational and expressive freedom. This paper does not propose total restriction but rather supports transparency requirements, friction-based design changes, and algorithmic accountability as minimally intrusive corrective mechanisms. Second are issues related to distributive justice that come up because economic burdens are not equally shared. A heatmap analysis shows how productivity losses and public-sector costs are pushed onto parties other than the immediate consumers of digital services. From a political-economy viewpoint, it is an instance where private profit capture does not align with social distribution of costs. Using principles from welfare economics and corrective taxation theory, this asymmetry makes a stronger case for platform responsibility mechanisms involving internalization instruments like digital externality levies or co-financing public mental health and digital literacy programs. The ethical question is not about whether platforms create value but about whether the way costs are distributed is fair under a decentralized profit-maximizing system. Third, we must look at the responsibility of digital platforms in terms of institutional design and incentive alignment. Behavioral dependence, as defined in this study, is reinforced by engagement-maximizing algorithms that monetize attention. This creates a structural incentive conflict between private revenue models and long-run social welfare. Drawing on political-economic theories of regulatory capture and market failure, the ethical challenge concerns governance architecture rather than individual morality. Policy responses should therefore focus on transparency mandates, algorithmic auditing, and incentive realignment rather than solely on user-level behavioral correction[10,12,13,15,16,22–26,27,80–84]. These three challenges—paternalism, distributive justice, and institutional responsibility—follow directly from the empirical asymmetry identified in the analysis. They provide a normative foundation for the policy recommendations advanced in Section 5 and replace rhetorical speculation with structured ethical evaluation.

8. Results

To operationalize the economic implications of digital addiction and move beyond purely narrative exposition, this study employs a visual aggregation of cost channels using a heatmap representation. The objective of this visualization is not econometric inference, but systematic comparison of relative intensities across economic dimensions and affected agents. By mapping multiple cost categories against key economic stakeholders, the heatmap facilitates an integrated assessment of how digital dependence generates private, organizational, and social burdens simultaneously. The heatmap summarizes the relative magnitude of economic costs associated with digital addiction across seven analytically distinct categories—direct expenditures, time-valued costs, opportunity costs, productivity losses, household spillovers, fiscal burdens, and platform-induced frictions—evaluated against five principal economic actors: individuals, households, employers, health systems, and society at large. Values represent standardized intensity scores derived from theoretical weighting and synthesis of the reviewed literature, rather than primary micro-level estimation. This visual approach serves three analytical purposes. First, it highlights the multi-layered diffusion of economic costs, illustrating how individual-level behavioral dependence scales into organizational inefficiencies and public-sector pressures. Second, it exposes asymmetries in cost allocation, revealing that certain stakeholders bear disproportionate burdens despite not directly generating the addictive dynamics. Third, it supports the section's central claim that digital addiction constitutes an economic pathology, characterized by cumulative inefficiencies and negative externalities, rather than an isolated behavioral anomaly. Accordingly, the heatmap should be interpreted as a conceptual diagnostic tool, designed to structure policy discussion and guide future empirical work, rather than as a definitive measurement of causal magnitudes.

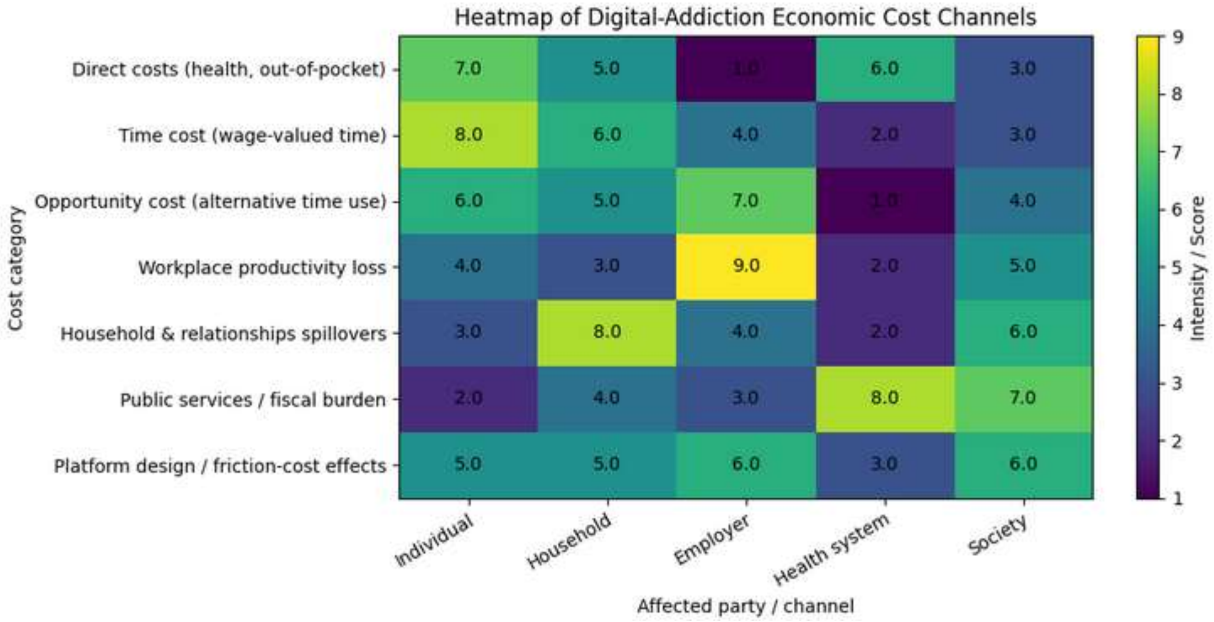

Figure 2. Digital-addiction economic cost channels (Authors' scheme).

Figure 2 illustrates a clear concentration and transmission of economic costs associated with digital addiction across both cost categories and affected stakeholders. High-intensity values observed in the dimensions of time-valued costs, opportunity costs, and workplace productivity losses indicate that the primary economic impact emerges through misallocation of human capital and erosion of effective labor input, rather than through direct monetary expenditures alone. Notably, the visualization reveals that while individuals initially generate the behavioral demand underlying digital dependence, employers, households, and public systems absorb a substantial share of the resulting costs. Elevated intensity levels in household spillovers and productivity loss channels suggest that private behavioral choices propagate into organizational inefficiencies and relational externalities, confirming the presence of second-order economic effects. The fiscal and health-system columns display consistently high intensities across multiple cost categories, underscoring the role of digital addiction as a latent public-finance stressor. These patterns imply that public institutions function as residual cost bearers when market mechanisms fail to internalize attention-extraction externalities embedded in platform design. Importantly, the dispersion of intensities across stakeholders is asymmetric rather than uniform, indicating that digital addiction does not produce proportional economic burdens. Instead, costs accumulate non-linearly, reinforcing systemic inefficiencies over time. This asymmetry supports the characterization of digital addiction as an economic pathology, wherein micro-level behavioral distortions generate macro-level welfare losses. The heatmap should be interpreted as a structural representation of economic pressure points, not as a causal or econometric estimate. Its analytical value lies in identifying where policy interventions—such as labor-time regulation, platform accountability, or preventative public-health investment—are likely to yield the greatest marginal economic benefit.

9. Discussion

Policy implications and recommendations are synthesized, placing findings in the context of action for policymakers, platform designers, and applied researchers. Core themes arising from the analyses are translated into guidance for interventions, supported by specification of lingering analytical gaps and suggestions for future empirical inquiry. A comprehensive assessment of digital addiction through an economic lens delivers practical ideas across many levels of concern. The analyses bring together various concepts and tools from economic theory, and the accumulated research effort should lay the foundations for subsequent empirical applications that explore the principal reflections in detail. The discussion focuses on the most policy-relevant aspects of the results by distinguishing among the following groups: governments, market regulators, digital service providers, public health professionals, and comparative-advantage analysts. A closing segment identifies concise topics for future exploration using the framework developed.

This research offers several methodological and conceptual strengths. First, it reframes digital addiction within a formal economic framework, moving beyond descriptive psychological narratives and grounding the discussion in welfare economics, time-allocation theory, and externality analysis. By integrating behavioral evidence with established economic concepts such as consumer surplus, opportunity cost, and social spillovers, the paper provides a coherent analytical structure capable of linking micro-level behavioral distortions to macro-level welfare implications. Second, the multidimensional mapping of cost categories against stakeholder groups introduces a structured diagnostic approach that highlights cost diffusion and asymmetry across the economic system. The heatmap visualization enhances interpretability by making complex interrelations transparent and facilitating comparative analysis without requiring immediate monetization. Third, the framework is designed to be extensible: researchers can replace the relative-intensity matrix with empirically estimated data while preserving the structural logic of the model, thereby enabling future empirical validation and policy simulation.

10. Strengths and limitations

At the same time, several methodological limitations should be acknowledged. The heatmap relies on structured, author-assigned relative intensity scores derived from literature synthesis rather than on primary econometric estimation or monetized cost calculations. While this approach supports conceptual clarity and comparative visualization, it does not provide causal identification or statistical inference. The framework therefore functions as a diagnostic and exploratory tool rather than as a definitive quantitative measurement of aggregate economic loss. In addition, the classification of cost channels and stakeholders, although theoretically grounded, necessarily involves interpretive judgment in mapping literature contributions to specific intersections. The absence of longitudinal or cross-country empirical calibration further limits the capacity to assess dynamic effects or institutional heterogeneity. Finally, because digital addiction remains conceptually contested across disciplines, the translation of behavioral constructs into economic categories may not capture all psychological or sociological nuances. Taken together, these limitations do not undermine the analytical contribution of the study but rather delineate its scope. The present framework establishes a structured economic lens through which digital addiction can be systematically examined, while explicitly inviting future research to operationalize, quantify, and empirically test the proposed cost channels and policy implications.

11. Conclusion

Bringing digital addiction into an economic framework highlights its social costs, benefiting consumers and platforms alike. By linking behavioral dependence to a reduction in welfare—that is, by shaping models in which time devoted to digital products is consumed at an algebraically lower level of utility than would otherwise be the case—three interesting consequences follow.

The first concerns the measurement of these costs. They can be captured by combining the direct costs that individuals and households bear when they suffer from digital dependence, the time devoted to such behavior that is valued as a quantity deducted from the economy, and the social spillovers typically associated with negative externalities. Second, by merging these considerations into standard economic models of individuals' time allocation and habit formation, behavioral dependence can become one critical factor determining the choice of a specific intertemporal plan and shaping the consistency of preferences across time. The predicaments of people affected by this behavioral issue can then be resolved through the lens of behavioral economics. Third, the potential upside of including these social costs in economic models involves conducting cost-benefit analyses and policy simulations, which reveal how allocating digital product use ranks by decreasing economic returns and which set of upper percentages of time devoted to these services—decisions that otherwise seem arbitrary—produces the maximum social welfare.

Appendix I

The heatmap presented in **Figure 2** is based on a structured relative-intensity scoring procedure rather than primary econometric estimation. The objective of this scoring system is not to generate precise monetary valuations, but to provide a standardized comparative representation of the diffusion and concentration of economic costs across categories and stakeholders. The construction of the intensity matrix followed three sequential steps. First, the literature reviewed in Sections 2–5 was systematically classified into seven cost categories (direct expenditures, time-valued costs, opportunity costs, productivity losses, household spillovers, fiscal burdens, and platform-induced friction costs) and five stakeholder groups (individuals, households, employers, health systems, and society). Each referenced study was mapped to one or more cost channels depending on whether it provided empirical evidence, conceptual support, or policy-related implications relevant to that channel. Second, relative salience weights were assigned to each cost–stakeholder intersection using a qualitative-to-quantitative translation rule. Specifically, intersections strongly supported by multiple empirical studies and theoretical arguments were assigned higher intensity values (8–10), intersections supported by moderate or indirect evidence received mid-range values (4–7), and intersections with limited or emerging evidence were assigned lower values (1–3). The scoring reflects comparative emphasis and structural importance within the reviewed literature rather than absolute magnitude or monetary measurement. Third, scores were normalized on a common 0–10 scale to ensure cross-category comparability. The resulting matrix therefore represents a structured synthesis index derived from literature density, theoretical centrality, and inferred economic transmission strength. It should be interpreted as a diagnostic visualization tool that highlights relative burden distribution patterns rather than as a causal or statistically estimated dataset. Reproducibility is ensured through (i) explicit definition of cost categories and stakeholder groups, (ii) transparent description of the scoring criteria, and (iii) the inclusion of the Python code used to generate the heatmap visualization. Researchers wishing to replicate or extend the framework may substitute the intensity matrix with empirically estimated coefficients or monetized cost data while preserving the same structural mapping procedure.

Follow the Python code:

```
# Constantinos Challoumis (C)(R) 2025 All Rights Reserved
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

# -----------------------------
# OPTION A (quick demo data)
# Rows = "Cost categories"
# Cols = "Economic channels / stakeholders"
```

```
# Values = intensity/score (e.g., 0–10, % impact, index, survey mean)
# -----------------------------
rows = [
    "Direct costs (health, out-of-pocket)",
    "Time cost (wage-valued time)",
    "Opportunity cost (alternative time use)",
    "Workplace productivity loss",
    "Household & relationships spillovers",
    "Public services / fiscal burden",
    "Platform design / friction-cost effects"
]

cols = [
    "Individual",
    "Household",
    "Employer",
    "Health system",
    "Society"
]

# Example intensity matrix (replace with your real numbers)
data = np.array([
    [7, 5, 1, 6, 3],
    [8, 6, 4, 2, 3],
    [6, 5, 7, 1, 4],
    [4, 3, 9, 2, 5],
    [3, 8, 4, 2, 6],
    [2, 4, 3, 8, 7],
    [5, 5, 6, 3, 6],
], dtype=float)

df = pd.DataFrame(data, index=rows, columns=cols)

# -----------------------------
# Heatmap plot (matplotlib only)
# -----------------------------
fig, ax = plt.subplots(figsize=(10, 5))
im = ax.imshow(df.values, aspect="auto")

# Ticks & labels
ax.set_xticks(np.arange(df.shape[1]))
ax.set_yticks(np.arange(df.shape[0]))
ax.set_xticklabels(df.columns)
ax.set_yticklabels(df.index)

# Rotate x labels for readability
plt.setp(ax.get_xticklabels(), rotation=30, ha="right", rotation_mode="anchor")
```

```
# Annotate cells with values
for i in range(df.shape[0]):
    for j in range(df.shape[1]):
        ax.text(j, i, f"{df.iat[i, j]:.1f}", ha="center", va="center")

# Colorbar and titles
cbar = fig.colorbar(im, ax=ax)
cbar.set_label("Intensity / Score")

ax.set_title("Heatmap of Digital-Addiction Economic Cost Channels")
ax.set_xlabel("Affected party / channel")
ax.set_ylabel("Cost category")

plt.tight_layout()
plt.show()
```

Conflict of interest

The authors declare no conflict of interest.

References

1. Karakose T, Yildirim B, Tülübaş T, Kardaş A. A comprehensive review on emerging trends in the dynamic evolution of digital addiction and depression. Front Psychol 2023;14. https://doi.org/10.3389/fpsyg.2023.1126815.
2. Berthon P, Pitt L, Campbell C. Addictive De-Vices: A Public Policy Analysis of Sources and Solutions to Digital Addiction. J Public Policy Mark 2019;38:451–68. https://doi.org/10.1177/0743915619859852.
3. Dresp B, Hutt A. Digital Addiction and Sleep. Int J Environ Res Public Health 2022;19. https://doi.org/10.3390/ijerph19116910.
4. Kuss D, Gainsbury SM. Debate: Behavioural addictions and technology use - risk and policy recommendations for problematic online gambling and gaming. Child Adolesc Ment Health 2021. https://doi.org/10.1111/camh.12449.
5. Allcott H. Digital Addiction. AEA Randomized Control Trials 2020. https://doi.org/10.1257/rct.5796-1.2000000000000002.
6. Weinsztok S, Brassard S, Balodis I, Martin L, Amlung M. Delay Discounting in Established and Proposed Behavioral Addictions: A Systematic Review and Meta-Analysis. Front Behav Neurosci 2021;15. https://doi.org/10.3389/fnbeh.2021.786358.
7. Bhattacharya D. Nonparametric Approaches to Empirical Welfare Analysis. J Econ Lit 2024. https://doi.org/10.1257/jel.20221534.
8. Chung S, Lee H. Public Health Approach to Problems Related to Excessive and Addictive Use of the Internet and Digital Media. Curr Addict Reports 2022;10:69–76. https://doi.org/10.1007/s40429-022-00458-z.
9. Graziano M, Platino V. A measure of social loss for production economies with externalities. Econ Theory 2024;78:443–74. https://doi.org/10.1007/s00199-024-01574-9.
10. Valasek C. Disciplining the Akratic user: Constructing digital (un) wellness. Mob Media Commun 2021;10:235–50. https://doi.org/10.1177/20501579211038796.
11. Brynjolfsson E, Collis A, Eggers F. Using massive online choice experiments to measure changes in well-being. Proc Natl Acad Sci U S A 2018;116:7250–5. https://doi.org/10.1073/pnas.1815663116.
12. Van Endert TS. Addictive use of digital devices in young children: Associations with delay discounting, self-control and academic performance. PLoS One 2021;16. https://doi.org/10.1371/journal.pone.0253058.
13. Hause J. The Theory of Welfare Cost Measurement. J Polit Econ 1975;83:1145–82. https://doi.org/10.1086/260387.
14. Acuff S, Mackillop J, Murphy J. Applying Behavioral Economic Theory to Problematic Internet Use: An Initial Investigation. Psychol Addict Behav 2018;32:846. https://doi.org/10.1037/adb0000404.
15. Di Pietro C, Graziano M, Platino V. Social loss with respect to the core of an economy with externalities. Econ Theory 2020;73:487–508. https://doi.org/10.1007/s00199-020-01293-x.
16. Zhao M, Wang S, Xia T. The social welfare effect of e-commerce product reputation information asymmetry from the perspective of network externality. PLoS One 2025;20. https://doi.org/10.1371/journal.pone.0313852.
17. Kitchener S, Zoe T. Digital Addiction in Teenagers: Tackling it With an App Based on Behavioral Economics. J Student Res 2021;10. https://doi.org/10.47611/jsrhs.v10i1.1329.

18. Frischmann B, Ramello G. Externalities, scarcity, and abundance. Front Res Metrics Anal 2023;7. https://doi.org/10.3389/frma.2022.1111446.
19. Acuff S, Pilatti A, Collins M, Hides L, Thingujam N, Chai W, et al. Reinforcer pathology of internet-related behaviors among college students: Data from six countries. Exp Clin Psychopharmacol 2021. https://doi.org/10.1037/pha0000459.
20. Willig R. Consumer's Surplus Without Apology. Am Econ Rev 1976;66:589–97.
21. Shiferaw BD, Tang J, Wang Y, Wang Y, Wang Y, Mackay L, et al. Impact of digital addiction on youth health: A systematic review and meta-analysis. J Behav Addict 2025;14:1129–58. https://doi.org/10.1556/2006.2025.00081.
22. Şan İ, Karsak HO, İzci E, Öncül K. Internet addiction of university students in the Covid-19 process. Heliyon 2024;10. https://doi.org/10.1016/j.heliyon.2024.e29135.
23. Li K. Market Power and Consumer Welfare: A Theoretical Analysis of Imperfect Competition. Adv Econ Manag Polit Sci 2025. https://doi.org/10.54254/2754-1169/2025.bj25114.
24. Alimoradi Z, Broström A, Potenza M, Lin C, Pakpour A. Associations Between Behavioral Addictions and Mental Health Concerns During the COVID-19 Pandemic: A Systematic Review and Meta-analysis. Curr Addict Reports 2024;11:565–87. https://doi.org/10.1007/s40429-024-00555-1.
25. Fleurbaey M, Kanbur R, Viney B. Social Externalities and Economic Analysis. Soc Res An Int Q 2020;88:171–202. https://doi.org/10.22004/ag.econ.309990.
26. Rung J, Madden G. Experimental Reductions of Delay Discounting and Impulsive Choice: A Systematic Review and Meta-Analysis. J Exp Psychol Gen 2018;147:1349. https://doi.org/10.1037/xge0000462.
27. Corchón L, Torregrosa R. Two extensions of consumer surplus. SERIEs 2020;13:557–79. https://doi.org/10.1007/s13209-021-00245-5.
28. Amlung M, Vedelago L, Acker J, Balodis I, Mackillop J. Steep delay discounting and addictive behavior: a meta-analysis of continuous associations. Addiction 2017;112:51. https://doi.org/10.1111/add.13535.
29. Cornes R. Externalities and Public Goods. Prices Quant 2020. https://doi.org/10.1017/cbo9780511571725.011.
30. Challoumis C. The R.B.Q. (Rational, Behavioral and Quantified) Model. Ekonomika 2019;98:6–18. https://doi.org/10.15388/ekon.2019.1.1.
31. Challoumis C, Eriotis N. A historical analysis of the banking system and its impact on Greek economy. Edelweiss Appl Sci Technol 2024;8:1598–617.
32. Marsch L. Digital Health and Addiction. Curr Opin Syst Biol 2020;20:1–7. https://doi.org/10.1016/j.coisb.2020.07.004.
33. Brynjolfsson E, Kim ST, Oh JH. The Attention Economy: Measuring the Value of Free Goods on the Internet. Inf Syst Res 2023;35:978–91. https://doi.org/10.1287/isre.2021.0153.
34. Rambaud SC, Torrecillas MM, Maturo F. Editorial: Time discounting as a tool to assess addictive behaviors and other disorders. Front Public Heal 2023;11. https://doi.org/10.3389/fpubh.2023.1165175.
35. Winfree J, Watson P. The Welfare Economics of "Buy Local." Am J Agric Econ 2017;99:971. https://doi.org/10.1093/ajae/aaw104.
36. Gritenco E, Şeptiţchi V, Borsev I. Info-digital addiction: an interdisciplinary analysis of the phenomenon, its criteria, and consequences. Stud Univ Mold Ser Științe Ale Nat 2025. https://doi.org/10.59295/sum1(181)2025_14.
37. Dasgupta P, Southerton D, Ulph A, Ulph D. Consumer Behaviour with Environmental and Social Externalities: Implications for Analysis and Policy. Environ Resour Econ 2016;65:191–226. https://doi.org/10.1007/s10640-015-9911-3.
38. Alimoradi Z, Lotfi A, Lin C-Y, Griffiths M, Pakpour A. Estimation of Behavioral Addiction Prevalence During COVID-19 Pandemic: A Systematic Review and Meta-analysis. Curr Addict Reports 2022;9:486–517. https://doi.org/10.1007/s40429-022-00435-6.
39. Cooper K, Fabian M, Krekel C. New approaches to measuring welfare. Fisc Stud 2023. https://doi.org/10.1111/1475-5890.12333.
40. Miller B, Reed D, Amlung M. Reliability and validity of behavioral-economic measures: A review and synthesis of discounting and demand. J Exp Anal Behav 2023. https://doi.org/10.1002/jeab.860.
41. Hausman J, Newey W. Nonparametric Welfare Analysis. Annu Rev Econom 2017;9:521–46. https://doi.org/10.1146/annurev-economics-080315-015107.
42. Brown J, Sofis M, Zimmer S, Kaplan B. Delay discounting is associated with addiction and mental health measures while controlling for health behaviors and health barriers in a large US sample. Addict Behav Reports 2024;19. https://doi.org/10.1016/j.abrep.2024.100545.
43. Hendren N. Welfare Analysis Meets Causal Inference. NBER Work Pap Ser 2020. https://doi.org/10.3386/w27640.
44. Shah SS, Shah SAH. Trust as a determinant of social welfare in the digital economy. Soc Netw Anal Min 2024;14:1–27. https://doi.org/10.1007/s13278-024-01238-5.
45. Theopilus Y, Mahmud A Al, Davis H, Octavia J. Persuasive strategies in digital interventions to combat internet addiction: A systematic review. Int J Med Inform 2024;195:105725. https://doi.org/10.1016/j.ijmedinf.2024.105725.

46. Cemiloglu D, Almourad M, Mcalaney J, Ali R. Combatting digital addiction: Current approaches and future directions. Technol Soc 2022. https://doi.org/10.1016/j.techsoc.2021.101832.
47. Johansson M, Romero D, Jakobson M, Heinemans N, Lindner P. Digital interventions targeting excessive substance use and substance use disorders: a comprehensive and systematic scoping review and bibliometric analysis. Front Psychiatry 2024;15. https://doi.org/10.3389/fpsyt.2024.1233888.
48. Revathi R, Paulraj T. An Empirical Study on the Consumers Behaviour and Economic Loss. Shanlax Int J Arts, Sci Humanit 2025. https://doi.org/10.34293/sijash.v12i4.8202.
49. Tucker J, Buscemi J, Murphy J, Reed D, Vuchinich R. Addictive behavior as molar behavioral allocation: Distinguishing efficient and final causes in translational research and practice. Psychol Addict Behav 2022. https://doi.org/10.1037/adb0000845.
50. Gao Z, House L, Bi X. Impact of satisficing behavior in online surveys on consumer preference and welfare estimates. Food Policy 2016;64:26–36. https://doi.org/10.1016/j.foodpol.2016.09.001.
51. Taylor K. The social diagnoses of digital addictions: Technophobic ambivalences, the limits of the natural and imperatives of self-governance in the information age. Sociol Health Illn 2023. https://doi.org/10.1111/1467-9566.13624.
52. Bernheim B, Taubinsky D. Behavioral Public Economics. Decis Financ Decis 2018. https://doi.org/10.1016/bs.hesbe.2018.07.002.
53. Goslar M, Leibetseder M, Muench H, Hofmann S, Laireiter A. Treatments for internet addiction, sex addiction and compulsive buying: A meta-analysis. J Behav Addict 2020;9:14–43. https://doi.org/10.1556/2006.2020.00005.
54. Challoumis C. From Economics to Economic Engineering (The Cycle of Money): The case of Romania. Cogito 2024;XVII:161–70.
55. Challoumis C. FROM SAVINGS TO ESCAPE AND ENFORCEMENT SAVINGS. Cogito 2023;XV:206–16.
56. Amendola N, Vecchi G. Durable goods and welfare measurement. J Econ Surv 2021. https://doi.org/10.1111/joes.12480.
57. Perali F, Piccoli L. An Extended Theory of Rational Addiction. Mathematics 2022. https://doi.org/10.3390/math10152652.
58. Lima V, Gaspar F. Beyond Marx: Externalities in the Age of Tech Oligarchy and Digital Class Struggle. Brazilian J Bus 2025. https://doi.org/10.34140/bjbv7n2-042.
59. Boumparis N, Haug S, Abend S, Billieux J, Riper H, Schaub M. Internet-based interventions for behavioral addictions: A systematic review. J Behav Addict 2022;11:620–42. https://doi.org/10.1556/2006.2022.00054.
60. Ng Y. Welfare Economics: Towards a More Complete Analysis 2003. https://doi.org/10.1057/9781403944061.
61. Vuchinich R, Tucker J, Acuff S, Reed D, Buscemi J, Murphy J. Matching, behavioral economics, and teleological behaviorism: Final cause analysis of substance use and health behavior. J Exp Anal Behav 2022. https://doi.org/10.1002/jeab.815.
62. Reinsdorf M. Measuring Economic Welfare. Policy Pap 2020. https://doi.org/10.5089/9781513544588.007.
63. Xu J. Digital health tools and habit formation: Investigating the role of anti-addiction systems in mitigating social media dependency. Int J Innov Res Sci Stud 2025. https://doi.org/10.53894/ijirss.v8i2.6007.
64. Jackson M, Rogers B, Zenou Y. Networks: An Economic Perspective. IO Theory EJournal 2016.
65. Chen Y. The Impact of Behavioral Economics on Consumer Decision-Making in the Digital Era. Adv Manag Intell Technol 2025. https://doi.org/10.62177/amit.v1i3.391.
66. Bickel W, Koffarnus M, Moody L, Wilson G. The behavioral- and neuro-economic process of temporal discounting: A candidate behavioral marker of addiction. Neuropharmacology 2014;76:518–27. https://doi.org/10.1016/j.neuropharm.2013.06.013.
67. Shirley SM. Profit and Public Value: A Welfare Comparison of Enterprise Models. J Res Humanit Soc Sci 2025. https://doi.org/10.35629/9467-1309177183.
68. Lin Z. Understanding Consumer Behavior: Integrating Economic Constraints and Behavioral Insights. Adv Econ Manag Polit Sci 2025. https://doi.org/10.54254/2754-1169/2025.bl23698.
69. Nosenzo D, Görges L. Measuring Social Norms in Economics: Why It Is Important and How It Is Done. Anal Krit 2020;42:285–312. https://doi.org/10.1515/auk-2020-0012.
70. Bickel W, Miller M, Yi R, Kowal B, Lindquist D, Pitcock J. Behavioral and neuroeconomics of drug addiction: competing neural systems and temporal discounting processes. Drug Alcohol Depend 2007;90 Suppl 1. https://doi.org/10.1016/j.drugalcdep.2006.09.016.
71. Brynjolfsson E, Collis A, Diewert E, Eggers F, Fox K. Gdp-B: Accounting for the Value of New and Free Goods in the Digital Economy. Macroecon Natl Income Prod Accounts EJournal 2019. https://doi.org/10.2139/ssrn.3356697.
72. Zhang Y, Zhang T. The Economics of Information Pollution in the Age of AI: A General Equilibrium Approach to Welfare, Measurement, and Policy. ArXiv 2025;abs/2509.1. https://doi.org/10.48550/arxiv.2509.13729.
73. Acuff S, Mackillop J, Murphy J. A contextualized reinforcer pathology approach to addiction. Nat Rev Psychol 2023;2:309–23. https://doi.org/10.1038/s44159-023-00167-y.

74. Wu D, Lee J-Y, Wang LF s. Positive Network Externalities and Negative Environmental Externalities in a Differentiated Duopoly With Entry Fee-Refund Policy. Am J Econ Sociol 2025. https://doi.org/10.1111/ajes.12631.
75. Martens B. Data Access, Consumer Interests and Social Welfare: An Economic Perspective. IO Product 2020. https://doi.org/10.2139/ssrn.3605383.
76. Lopez-Guzman S, Konova A, Louie K, Glimcher P. Risk preferences impose a hidden distortion on measures of choice impulsivity. PLoS One 2018;13. https://doi.org/10.1371/journal.pone.0191357.
77. Brynjolfsson E, Hu YJ, Smith M. Consumer Surplus in the Digital Economy: Estimating the Value of Increased Product Variety at Online Booksellers. MIT Sloan Sch Manag Work Pap Ser 2003. https://doi.org/10.2139/ssrn.400940.
78. Challoumis C. Index of the cycle of money: The case of Costa Rica. Sapienza 2023;4:1–11.
79. Challoumis C, Eriotis N. The Impact of Artificial Intelligence on the Greek Economy. J Open Innov Technol Mark Complex 2025;11:1–13. https://doi.org/https://doi.org/10.1016/j.joitmc.2025.100578.
80. Tasnádi A, Smith TG. A Theory of Natural Addiction 2007.
81. Faust K, Faust D. Refining Measures for Assessing Problematic/Addictive Digital Gaming Use in Clinical and Research Settings 2015.
82. Karakose T, Tülübaş T, Papadakis S. Revealing the Intellectual Structure and Evolution of Digital Addiction Research: An Integrated Bibliometric and Science Mapping Approach 2022.
83. Ellis DA, Kaye LK, Wilcockson TDW, Ryding FC. Digital Traces of Behaviour Within Addiction: Response to Griffiths (2017) 2018.
84. Helmersson Bergmark K, Bergmark A, Findahl O. Extensive Internet Involvement—Addiction or Emerging Lifestyle? 2011.
85. Challoumis C. Integrating Money Cycle Dynamics and Economocracy for Optimal Resource Allocation and Economic Stability. J Risk Financ Manag 2024;17:1–25. https://doi.org/10.3390/jrfm17090422.
86. Challoumis C. Rewarding taxes on the cycle of money. vol. 5. 2024.
87. Challoumis C. THE INFLATION ACCORDING TO THE CYCLE OF MONEY (C.M.). Econ Altern 2025;2025:324–53. https://doi.org/https://doi.org/10.37075/EA.2025.2.03.
88. Challoumis C. The impact factor of Tangibles and Intangibles of controlled transactions on economic performance. Econ Altern 2025;31:64–76.
89. Just R, Hueth D, Schmitz A. The Welfare Economics of Public Policy: A Practical Approach to Project and Policy Evaluation 2005.