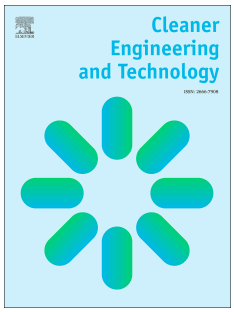
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Time, Technology, and Energy: The energy impacts of digitally-enabled automation in everyday life

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PII: S2666-7908(26)00205-3

DOI: https://doi.org/10.1016/j.clet.2026.101346

Reference: CLET 101346

To appear in: *Cleaner Engineering and Technology*

Received Date: 4 January 2026

Revised Date: 27 October 2026

Accepted Date: 27 October 2026

Please cite this article as: Bieser, J., Vrain, E., Time, Technology, and Energy: The energy impacts of digitally-enabled automation in everyday life, *Cleaner Engineering and Technology*, https://doi.org/10.1016/j.clet.2026.101346.

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Time, Technology, and Energy: The energy impacts of digitally-enabled automation in everyday life

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Abstract

Digital technologies such as AI, robotics, and sensors are increasingly used to automate everyday activities, ranging from chores enabled by robot vacuums to leisure and mobility through personalized content recommendations and trip planners. These applications are typically framed in terms of time savings and convenience. However, as automation reshapes individual time-use patterns, the daily sequence of activities, it also influences the energy impacts of lifestyles, since activities have varying energy demands. This paper conceptually analyses the energy impacts of digitally-enabled automation in private life through a mixed methods phased and iterative approach. We show that automation's energy impact depends on changes in both the time and energy intensity of the automated and any affected substitute activities. Automation in chores typically saves time as machines replace human execution, while in leisure it often involves close human-machine collaboration, extending capabilities to support a greater intensity of activities. The largest energy-saving potentials lie in automated devices consuming less energy than their manual counterparts or by directing people away from high-energy activities toward more efficient options through appealing features. A key risk is that tasks previously without energy use become dependent on energy-consuming devices, leading to a materialization and electrification of activities. Also, with automation, tasks no longer requiring human attention can be carried out simultaneously alongside other activities, with their energy consumption accumulating. Thus, as automation expands, it is crucial to promote energy-saving strategies, or else it may drive greater use of energy-intensive devices and increase overall lifestyle energy use.

Keywords

Automation, energy consumption, time use, lifestyles, sustainability, digitalization, everyday life

Highlights

- Automation alters time and energy use of chore, leisure and mobility activities
- Chore automation saves time; leisure automation intensifies activities
- Automation can save energy through more energy efficient devices
- Automation increases energy use through electrification and parallelization of tasks

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1. Introduction

1.1 Motivation

Digital information and communication technology (ICT) has penetrated society to an extent that lets people structure their lives around the possibilities it provides, a process called digitalization (Brennen & Kreiss, 2014). One of the key opportunities presented by digitalization is automation—"the execution by a machine agent (usually a computer) of a function that was previously carried out by a human" (Parasuraman & Riley, 1997, p. 231). Although established technologies, such as internal combustion engines and electric motors, have long been used to automate tasks like dishwashing or production lines, digital technologies such as sensors, robotics, intelligent algorithms, and data transmission networks are increasingly central drivers of automation development. The rapid advancement of their capabilities, including the large-scale acquisition of contextual data, fast and increasingly energy-efficient data processing for context-aware decision-making, and the ability to translate decisions into actions in real time across digital and physical environments, has contributed to a growing automation of manual tasks (IEA, 2025).

While there has been a strong focus on digitally-enabled automation of industrial production and workplace processes over the last few decades, often framed under the Industry 5.0 paradigm (Alexander, 1985; Barata & Kayser, 2023), applications have significantly expanded into non-work related activities. These include applications in chores, such as automated kitchen appliances, robot vacuum cleaners, and robotic lawnmowers (Müller et al., 2024), or in leisure such as AI-based image generators, automated video processors or smart playlists that automatically select songs based on music taste (Jadhav et al., 2024). These applications are typically framed in terms of time savings and convenience. However, as automation reshapes individual time-use

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patterns, referring to the daily sequence of activities such as sleeping, household chores, or leisure activities (Jalas, 2002), it also influences the energy impacts of personal lifestyles, since different activities require varying amounts of energy. For example, driving a car consumes fuel, watching TV uses electricity, and even sleeping can involve energy use for heating residential buildings.

From a time-use perspective, automation affects energy use in two ways. First, it can change the energy demand of automated activities, for example, self-driving cars need extra digital hardware but may drive more efficiently (Taiebat et al., 2018). Second, by saving time, automation allows individuals to engage in other activities, which may also contribute to energy use, creating so-called time rebound effects, which occur when increases in time efficiency lead to an overall increase in energy use (Bieser, 2020; Mizobuchi & Yamagami, 2022; Sorrell & Dimitropoulos, 2008). Thus, the energy impacts of automation in private life depend on how it changes the time and energy use of both automated and substitute activities, making these effects hard to predict (Vrain et al., 2026).

Because automation applications are evolving rapidly in both number and variety, empirical evidence on their time and energy impacts remains scarce, and a clear conceptual understanding of their risks and opportunities for low-energy lifestyles is still lacking. This article addresses this need and aims to identify the key opportunities and risks of digitally-enabled automation in everyday life and to outline recommendations for researchers and practitioners for aligning automation use with energy reduction goals.

1.2 Key outcomes

This paper makes four key contributions.

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First, it provides the only current overview of digital automation applications in private life, identifying 36 activities across chores, leisure, and mobility with market-available execution-stage automation (Section 4).

Second, it develops a conceptual framework for systematically analysing how automation affects time use and, through it, the energy-intensity of everyday life. (Section 5). Researchers and practitioners can use it to assess the potential time and energy effects of automation applications and identify where energy-saving opportunities or rebound risks are likely to emerge.

Third, it provides an example application of the framework through a case study of robot vacuum cleaners (Section 6), showing that time savings do not automatically translate into energy savings, but may even increase energy use.

Fourth, it synthesizes key opportunities and risks of digital automation for energy savings and derives recommendations for researchers and practitioners to design and govern automation in line with energy-reduction goals (Section 7 and 8).

2. Related work

2.1. Time and energy effects of private life automation

Historically, automation applications have focused on industrial and military contexts where technologies have been developed to improve efficiency, productivity, safety and control in highly structured environments (Carr, 2016; Parasuraman et al., 2000; Sheridan & Verplank, 1987). However, in recent decades, automation has rapidly expanded into private spheres, altering both the nature and timing of everyday activities. The literature on automation has evolved in parallel with these developments. Levels of automation (LOA) taxonomies define how tasks can be shared or transferred between human and machine along a continuum from manual to fully autonomous (Barbieri et

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al., 2022; de Visser et al., 2018; Jin et al., 2025; Kim & Zhang, 2025; Vagia et al., 2016). While these taxonomies have served domains such as engineering, aviation and ergonomics, they rarely account for how automation reshapes the structure of daily routines or the sequencing of time use. Notably, out of the 15 automation taxonomies reviewed by Vagia et al. (2016), none explicitly examine the temporal impacts of automation in the private sphere.

However, there are studies that indicate that private life automation applications can have complex and unintended consequences for everyday routines as users adopt these technologies in ways that diverge from designers' expectations (Parasuraman et al., 2000; Vrain & Wilson, 2024). For example, Carr (2016, p. 67) summarizes what scholars term "the substitution myth", the idea that a labour-saving device doesn't just provide a substitute for some isolated component of a job, it alters the character of the entire task, including the roles attitudes and skills of the people who take part in it. Similarly, Hertog et al (2023) point out that earlier private life technologies, such as those improving hygiene or nutrition, often led to higher standards and expectations, rather than reducing workload. They also estimate that private life automation could save individuals between 1.5 to 3 hours on a typical weekday; however, they do not explore how this freed time might instead be reallocated, for example, toward leisure, care or additional household tasks.

Only a few studies have empirically examined the time and energy effects of automation in private life, and these focus on a narrow range of applications, such as self-driving vehicles (Kontar et al., 2026; Rebalski & Johansson, 2024; Wadud et al., 2016), robot vacuum cleaners (Mizobuchi & Hiroaki, 2024; Nicholls & Strengers, 2019; Vrain et al., 2026), and smart energy management systems (Fabi et al., 2017; Mahmood et al., 2024; Sozer & Tuysuz, 2020). For instance, self-driving vehicles may improve

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the time and energy efficiency of travel, but greater convenience and accessibility can also trigger rebound effects, increasing travel demand and overall energy use (Kontar et al., 2026; Wadud et al., 2016). Mizobuchi and Yamagami (2024) found that robot vacuum cleaners shifted time toward other activities which offset the device's energy savings. In a related study, they showed that online grocery delivery increased leisure time without raising electricity use, whereas time saved by dishwashers was partly reallocated to laundry, slightly increasing electricity consumption (Mizobuchi & Yamagami, 2022). Some studies have also looked at leisure automation but focused mainly on social aspects (e.g. well-being) neglecting potential energy consequences (Baranowski & Mroczkowska, 2021).

The results of these studies highlight that energy effects of private life automation depend on changes in the energy use and time spent on automated and any substitute activities. However, the existing evidence is limited to a small number of cases and broadly neglects the energy effects of automation in leisure. It does not support broader conclusions about the risks and opportunities of automation for energy-conserving lifestyles across domains such as mobility, household chores, and leisure.

2.2. Energy effects of automation from a time-use perspective

A valuable perspective to better understand the time and energy effects of automation in private life is the time-use approach introduced by Jalas (2002). He defined lifestyles as a series of time-consuming activities and estimated the energy use of these activities by allocating the energy consumption of the products and infrastructures used to perform them. He distinguishes between direct energy use during an activity, such as fuel for driving or electricity for watching TV, and indirect energy use, meaning the embodied or "grey" energy required to produce and dispose of the necessary products and infrastructure. While changes in time use directly affect direct

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energy requirements, indirect energy requirements are affected only when the production of goods increases or decreases. Applied to the context of automation, this means that the energy impact of automation depends on changes in the energy intensity (direct and indirect energy use per unit of time) of the automated activity, and changes in the duration of the automated activity and any substitute activities (time spent on activities).

Later studies have applied Jalas approach to energy use and CO_2e emissions across activities (Aall, 2011; De Lauretis et al., 2017; Druckman et al., 2012; Jalas & Juntunen, 2015; Smetschka et al., 2019; Yu et al., 2019). Although results vary by context, they consistently show that motorized transport and activities involving energy-intensive devices tend to have high direct energy use, while less frequent activities that rely on substantial infrastructure, such as visiting a stadium or museum, tend to have high indirect energy use (Bieser et al., 2022). Thus, if automation frees up time for other activities, the energy effects vary greatly depending on the type of activity and can lead to net energy savings or increases. For example, it has been shown that the increased use of ICT in households leads to people spending more time at home with ICT-based devices, thereby reducing energy-intensive transportation (Sekar et al., 2018).

Jalas's approach has also been used to study how digital applications affect time and energy use. For example, Lehner (2025) identifies three ICT-related time-use effects: displacement of existing activities, creation of new ICT-based activities, and modification of existing activities. Bieser and Hilty (2020) identify nine effects, including parallelization, substitution, avoidance, delegation, and changes in the duration, planning, and form of activities. However, these studies have not specifically examined the time and energy effects of digitally-enabled automation. The research discussed in the previous section on robot vacuum cleaners has implicitly or explicitly

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followed this perspective (Mizobuchi & Hiroaki, 2024; Vrain et al., 2026), but such work covers only a small subset of the many domestic automation applications now available. More broadly, no study has systematically assessed the impacts of automation, despite its growing importance as digitally-enabled applications continue to expand, along with their potential effects on time and energy use.

2.3. Research gaps and targets

To summarize, digitally enabled automation can have substantial and often unintended effects on individual time and energy use. Existing research on automation's time and energy effects remains limited, focusing mainly on legacy devices or a few isolated newer applications, such as robotic vacuum cleaners, while the broader and increasingly widespread field of domestic automation remains poorly understood.

This paper addresses that gap by examining how digitally-enabled automation may shape time and energy use and by identifying key opportunities and risks for energy-conserving lifestyles. Yet, we recognize that empirically measuring the effects would require extensive experiments and data collection beyond the scope of this study. We thus adopt an expert coding approach that allows to identify broader effect patterns despite limited empirical evidence. The study should therefore not be understood as a detailed empirical assessment of individual applications, but as an exploratory conceptual analysis of broader patterns that can guide future research and help inform policies for the energy-conscious deployment of digitally enabled automation.

3. Materials and methods

In this study, we adopted a mixed methods, phased and iterative approach, including a literature review to ground theory development in existing knowledge and to identify real-world applications, expert coding procedures to analyse real-world

applications, and a case study to demonstrate and illustrate the theory. Figure 1 provides an overview of the key steps, which are described in more detail in the following.

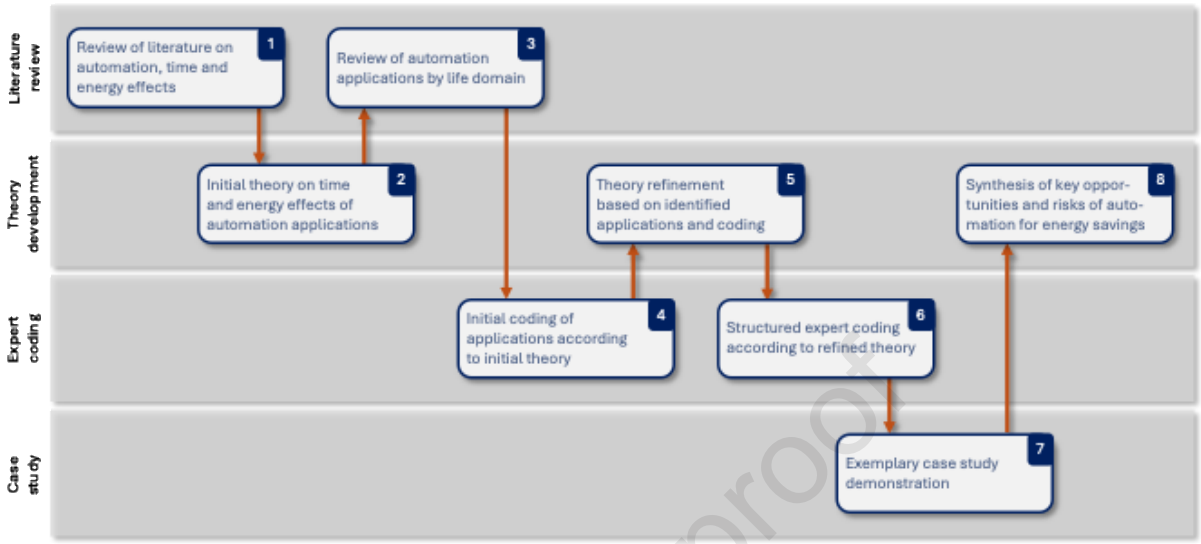


Figure 1. Research approach. The arrows show the sequence of activities. Each activity builds on all preceding steps.

After the initial literature review on time and energy effects of automation and digital technologies (step 1, see section 2.1 and 2.2), we began by outlining a fundamental distinction of potential time and energy impacts of digital automation applications (step 2). The initial conceptual framework described these effects at a high level, distinguishing three categories of applications based on their time-use effects ("replace," "assist," and "coordinate"; see Section 5), as well as two types of energy effects: increases or decreases in direct energy intensity, defined as energy use per unit of time. We focused on direct energy intensities because changes to indirect (or embodied) energy intensities are hard to predict as they depend on changes in the production of goods used to perform the activities.

In the third step, we compiled a comprehensive set of widely used automation applications from existing literature. To examine automation's time-use impacts, it is not only the application itself that matters, but also which human activity, previously

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performed manually, is affected by it. Thus, we started by reviewing literature that categorises activities of daily life, looking across multiple research fields (Court & Sorrell, 2020; Røpke & Christensen, 2012) and national surveys (Blank, 2019; Morris et al., 2023; ONS, 2016). Based on this review, we established a harmonised set of 14 daily life categories in three private life domains that are common in time-use research: leisure, chores and mobility. For each category, we identified digitally-enabled automation applications that are currently available on the market. It should be noted that this approach does not reflect a systematic literature review aimed at identifying all available applications. However, it allows for the identification of a large number of relevant applications across various life domains and thereby also allows to reveal differences in automation effects across these domains.

In the fourth step, we used an expert coding procedure for the data analysis, whereby experts evaluate applications based on clearly defined evaluation criteria and decision rules, which is a common approach in grounded theory and information systems research (Holton, 2010; Urquhart et al., 2010). As noted above, this method was deemed appropriate because empirical evidence on the effects of many applications on time and energy use remains limited, and systematically measuring the impacts of all applications empirically would be beyond the scope of this study.

Our coding team consisted of an interdisciplinary team of two researchers with complementary expertise and who are also the co-authors of this study. One researcher has extensive and documented experience in the environmental assessment of digital applications, particularly from a time-use perspective [source removed for anonymization]. The other researcher has extensive expertise in the study of (digital) automation and how it shapes everyday practices, including the associated implications for energy use [source removed for anonymization].

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In the initial coding round, one of us conducted the preliminary coding, which was subsequently reviewed and revised by the second researcher. The coding process and the subsequent discussions of disagreements proved highly productive, as they revealed differences in our understanding of the applications' functionalities and the manual tasks they replace. For example, a robo-advisor may either autonomously generate and implement investment decisions or support a person by creating personalized proposals, with the final decision made by the user. The time-use impacts depend on the features offered and how they are utilized. Based on these insights, we clarified each application and its goal, distinguished more precisely between its time-use effects, and substantially refined the framework in step 5. While the initial framework identified three types of time-use effects, the revised version distinguishes nine.

In the sixth step, we repeated the coding of the applications using the updated conceptual framework. This round was conducted in a more systematic manner than the initial coding process. First, we developed a set of clear coding questions and decision rules that allowed us to classify the applications according to the refined conceptual framework (see Appendix, Table 4 and 5). Then, we both coded the applications independently based on the framework. The resulting coding outcomes were then systematically compared using Cohen's Kappa, a standard measure of inter-coder agreement that accounts for agreement occurring by chance (Vach & Gerke, 2023). The average Cohen's Kappa across all criteria was 0.68 (indicating substantial agreement), with no criterion falling below 0.46 (moderate agreement). However, occasional disagreements between us occurred, which were discussed and resolved. Furthermore, a brief justification was written for each application, explaining why it was assigned to a specific category, to improve the comprehensibility of the classification for the reader.

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Overall, this indicates substantial inter-coder agreement but does not constitute an external validation of the coding process. Finally, we analysed all coding results to identify emerging patterns and differences in automation's effects on time use and energy use across the three life domains.

In the seventh step, we demonstrate our conceptual framework in a case study by assessing the net time and energy impacts of a relatively new yet increasingly adopted form of digitally-enabled automation, robot vacuum cleaners (The Business Research Company, 2026). In our analysis, we assess the effects of adopting this application on cleaning time and energy use, as well as on the reallocation of time to other activities and the associated energy use of those substitutes. Given that the choice of substitute activities is highly context-dependent, we account for this uncertainty in our calculations. A detailed description of the calculation methods and data sources is provided in Section 6 for clarity and transparency.

In the eighth and final step, we document the results and synthesize the key opportunities and risks of digitally-enabled automation for energy savings. This iterative yet structured approach developed a framework grounded in existing literature while maintaining its practical relevance and applicability.

4. Overview of private life automation applications

In total, we identified 36 activities which currently have execution-stage automation on the market, clustered in chores, leisure, and mobility (see Table 1). Unsurprisingly, most applications address chores, which are often viewed as routine and not requiring complex problem-solving (Lehdonvirta et al., 2023). These range from automated cleaning and cooking to support systems for shopping and building management, such as product recommenders and smart thermostats. Some of the chore

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applications also involve delegation from a principal user to an external contractor rather than purely automation, for example, cooking through food delivery services.

In leisure, a growing range of AI-based applications is emerging across information and education, such as news aggregators and language learning chatbots; digital media, including smart playlists that analyse listening habits and recommend new content; and creative activities, such as AI-powered writing tools, image editors, and music or video editing programs. These tools automate certain steps in the process while also enhancing users' capabilities, e.g. by providing additional functionalities that offer users new editing options and enable them to produce novel results. The third category of activities that are impacted by automation is mobility. Self-driving vehicle technology is anticipated to have a significant impact on travel behaviour in the coming years (Taiebat et al., 2018). In travel planning, many automation tools have already become mainstream, such as multimodal trip planning tools (e.g., Google Maps), flight booking tools, and hotel booking tools. Advances in AI now enable a deeper level of automation. For example, text generation tools are being used to plan specific (sightseeing) activities and entire daily itineraries at vacation destinations (Volchek & Ivanov, 2024).

When classifying applications by life domain, it is important to recognize that the perception of an activity can differ from person to person and even from one situation to another. For example, for some, cooking is seen as a necessary task, while for others, it offers an opportunity for relaxation or creative expression (Holmes, 2022). Traveling can also be work-related (e.g. commuting), a chore (e.g., shopping trips) or leisure (e.g., joyriding).

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Life domain	Category	Activity	End goal of the activity	Execution-stage automation axample	Example
Leisure	Communication, socialising	Message responding	The message is sent	AI-writing assistants	LinkedIn automated responses
		Blog writing	An article is finalized and published	AI text generators	ChatGPT auto-write
	Information search, provision	Browsing news websites	One is updated with the latest news	News aggregators	Yahoo News
		Finding reading materials	The next book to read is selected	Content recomm. systems	Amazon book recom.
	Entertainment, media	Selecting music for listening	Listening to music	Smart playlists	Spotify autoplay
		Selecting film/TV episode	The next movie to watch is selected	Smart watchlist	Netflix autoplay
	Health, fitness	Planning training programs	The training plan is finalized and ready to implement	AI training assistants	Freeletics Coach
		Health checks	Health data is collected	Fitness and health trackers	Fitbit heart monitoring
	Education, study, learning	Conversational language learning	One's language skills are improved	AI language learning chatbot	Duolingo Max
	Recreation, leisure, hobbies	Artmaking	An art piece is finalized and ready for publication	AI art generators	DALL·E
		Image/video editing	A video is edited and ready for publication	AI video editors	RunwayML
Chores	Managing home – hygiene, care, finances	Floor cleaning	The floor is clean	Robot vacuum cleaners	iRobot Roomba
		Clothes ironing	The clothes are ironed	Automatic ironing mach.	Scanovus
		Window cleaning	The windows are clean	Robotic window cleaners	Ecovac Winbot
		Paying bills	The bills are paid	Autom. bill payment sys.	Standing order
		Financial investing	The investment decision is taken and executed	Robo-advisors (with human approval)	Betterment
		Feeding pets	The pet is fed	Automated food dispenser	Petlibro
		Playing with pets	The pet is entertained	Robot pet companion	Oro
		Cutting the lawn	The lawns are mowed	Robot lawnmower	Robomow
		Garden watering	The plants continuously have sufficient water	Automated watering syst.	Gardena
	Retail – non-grocery	Shopping in general	The out-of-stock goods are ordered	Autom. restocking service	Amazon Dash
		Discovering products	The products are selected and bought	Product recommender sys.	Amazon
		Paying for products	The bill is paid	Just-walk-out technology	Amazon Go

	Retail – grocery	Grocery shopping	Groceries are delivered at the door	Grocery delivery apps	Ocado with pre-filled basket
		Meal planning	The meals for the next week are planned and ordered	Meal delivery services (subscription-based)	HelloFresh
	Managing home – lighting, devices, appliances (exc. food-related)	Locking doors and windows	The doors are locked or open	Smart locks (full presence-based automation)	VW Keyless Entry
		Switching lights	The lights are on/off as necessary	Smart lighting systems (full automation)	Philips Hue
	Managing home – cooking, dishwashing, other food-related	Food preparation	The meal is cooked and ready to eat	Autom. cooking appliances	Thermomix
		Brewing coffee	The coffee is ready to drink when desired	Automated coffee machines (with scheduling)	Jura Z10
	Managing home – heating, cooling, hot water, + own energy	Managing indoor climate	The room temperature is always comfortable	Smart thermostats (without overwrite)	Nest
		Air purification	The room climate is good	Automated air purifiers	Dyson Pure Cool
Mobility	Travel	Driving	One reaches their destination safely	Self-driving cars (level 4 automation)	Tesla Autopilot
		Collecting goods	Ordered goods arrive at the home	Delivery robots	Starship robots
		Ride-hailing	One reaches their destination with a ride hailing service	Ride-hailing services	Uber
	Pre-travel	Multimodal trip planning	The connection is decided upon	Mobility-as-a-Serv. apps	Citymapper
		Trip planning	The trip plan is finalized and ready to be implemented	Smart trip planners	Google Trips

Table 1. Categorized overview of devices and applications and the activities they automate by life domain.

5. Time-use and energy effects of automation applications

In the following, we present the refined conceptual framework that distinguishes the time-use and energy effects of digitally enabled automation, followed by the results of coding the real-world applications listed in Table 1 according to this framework.

5.1 Conceptual framework of time-use effects of automation applications

Existing taxonomies of levels of automation consider multiple aspects, such as which actor proposes decision options, which actor makes the final decision, and who carries out the execution (Simmler & Frischknecht, 2021; Vagia et al., 2016). Typically, they distinguish several categories of human–machine collaboration along a spectrum

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between two extreme scenarios: fully manual execution by a human and fully autonomous execution by a machine. From a time-use perspective, the division of tasks between humans and machines is also central, as whether automation saves time for humans depends on how their role changes as a result. Thus, we also defined two extreme scenarios, one in which the machine takes over the entire task and operates fully autonomously (called “Replace”). The opposite extreme is fully manual execution by a human (referred to as “Manual”), where no tasks are automated.

Theoretically, a continuum of intermediate scenarios exists between these two extremes, reflecting varying degrees of time savings for humans, which could be distinguished in great detail. However, for the purpose of classifying applications, such fine-grained differentiation was not practical, as no precise empirical data are available for all the applications under study. Consequently, we grouped all intermediate scenarios under the term “Assist,” indicating that both humans and machines play a role in executing the activity.

However, within the “Replace” and “Assist” categories, further conceptual distinctions can be made that are critical for human time savings and that were identified during the coding phases. Even when a machine fully takes over activity execution, a one-time initial setup of the automation application is often required, for instance, configuring automated lighting scenes or a smart thermostat to regulate heating autonomously (Becks et al., 2023). If this setup only occurs once and does not need to be repeated with each use, its impact on overall time savings is likely minimal. However, there are also applications where preparatory activities are performed before each application run, even though the application executes the actual task autonomously. For example, robotic vacuum cleaners often require objects to be cleared

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from the floor before operation or their dust containers to be emptied (Vrain et al., 2026).

While this distinction mainly concerns activities before task execution, human involvement may still be required during task execution even when a machine performs a task autonomously. Self-driving vehicles provide a clear example. Only at Level 5 automation can drivers fully engage in other activities in parallel. At lower automation levels, drivers must continuously monitor the driving process to ensure safety and be ready to intervene in unexpected situations (SAE International, 2016), significantly restricting the range of activities that can be performed simultaneously. For instance, making a phone call might be feasible, but attention-demanding tasks such as working on a laptop are not. And even when the vehicle operates fully autonomously (Level 5), the passenger must remain in the car as his or her transport is the purpose of the activity. This further limits the range of activities that can be performed simultaneously.

In fact, in many automation applications, the human is "in the loop," either confirming suggestions from the system or regularly reviewing results and making new requests. For example, when writing with AI text generators, humans often interact through a series of prompts, reviewing outputs, and refining the work (Zamfirescu-Pereira et al., 2023). This close collaboration with the machine means that no other tasks that require cognitive attention can be done simultaneously.

Still, the machine could help the human achieve the goal faster and thus save time. However, some automation applications do not just replicate a previously manual activity but also introduce additional features that can entice humans to spend more time engaging with the activity. Such applications can enhance human capabilities, altering both the way activities are performed and their outcomes. This is particularly evident in many modern AI applications such as AI writing assistants or image and video

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processing applications. The impact on time use depends on how these tools are employed. Some users might leverage them to accelerate task completion, effectively saving time, while others use the enhanced capabilities to improve outcomes, potentially spending the same amount of time or even more on the activity (Bieser, 2022; Raisch & Krakowski, 2021).

During our analysis, we also identified widely used applications in which the digital application does not perform the activity itself but facilitates delegating it from the user to a service provider, for example, cooking via food delivery apps or driving via ride hailing services. Although the activity itself is not automated, these applications can still generate significant time savings for the user and thus were considered.

Table 2 presents our refined conceptual framework of different forms of automation classified according to their impact on time use. It identifies nine distinct modes, which vary in the roles of humans and machines, the level of human involvement required, whether human presence is necessary, and consequently, the potential for reallocating time to other activities.

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Machine-human interaction	Role of machine	Role of human	Presence of humans during task execution required	Time -use impacts	Example applications
Replace	Machine takes over entire activity	No or one-off human involvement	No	Entire activity time is saved and can be spent on any other activity. Only initial set-up and configuration of the machine might be required.	Automated watering system
	Machine takes over entire activity	Human needs to do preparatory and/or follow-up activities	No	Entire activity time is saved and can be spent on any other activity minus some preparation time.	Robot vacuum cleaners
	Machine takes over entire activity	No or one-off human involvement	Yes	Entire activity time is saved and can be spent on activities that can be done in parallel.	Fully self-driving cars transporting humans (level 5 automation)
	Machine takes over entire activity	Human attention required	Yes	Only activities that do not impair focus can be done in parallel.	Self-driving cars transporting humans (level 4 automation)
Assist	Machine takes over parts of the activity	Humans still perform parts of the activity	Yes (at least for parts of the activity)	Some time is saved that can be spent on other activities that are done before, afterward or in parallel.	Automatic ironing machine
	Machine enhances activity through (additional) automated features	Humans still perform parts of the activity	Yes (at least for parts of the activity)	While automated features can save time, they can encourage users to spend more time engaging with it.	AI-image processor
Coordinate	Coordination between principal and contractor	Contractor takes over activity; principal needs to do preparatory and/or follow-up activities	Principal: No Contractor: Yes	Principal activity time is saved and can be spent on any other activity minus some preparation time	Grocery delivery apps
	Coordination between principal and contractor	Contractor takes over activity; principal needs to do preparatory and/or follow-up activities	Principal: Yes Contractor: Yes	Principal activity time is saved and can be spent on activities that can be done in parallel minus some preparation time	Ride-hailing services
Manual	None	Human performs entire task manually	Yes	No time savings for human	n/a by definition

Table 2. Forms of automation categorized by the roles assumed by humans and machines, whether human presence is required, and the potential for humans to reallocate their time to other activities.

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5.2 Results of the time-use effect coding of real-world applications

Figure 2 illustrates the classification of the automation applications according to the three forms of human–machine interaction, based on the structured expert coding process (detailed coding results by application are provided in Table 6 in the Appendix). As noted earlier, the specific effects depend on the exact application functionalities and usage patterns, which can evolve over time and are context dependent. Nevertheless, the analysis reveals several key patterns. It shows that "replace" applications dominate in chores, where many applications are clearly designed with timesaving in mind to reduce burdens, such as robot vacuum cleaners, watering systems, or automated payments. While some of those require some preparatory activities to start the application, human attention or presence is usually not required allowing the reallocation of saved time to other activities. In contrast, automation in leisure functions differently, with human–machine collaboration playing a central role rather than task replacement. This aligns with a frequently used definition of leisure activities which states that they cannot be delegated to others without the loss of utility (third-person criterion, Verbooy et al., 2018). Leisure automation often enhances the quality of the experience or capabilities rather than directly saving time (Baranowski & Mroczkowska, 2021). For instance, intelligent video and music playlists may speed up track selection, but they are not primarily intended to reduce the time spent consuming media. Likewise, AI-powered creative tools lower barriers to participation while encouraging longer engagement and experimentation. The only "leisure" application in our list that replaces human activity is a smart music playlist which automatically selects the next songs to play. Thus, automation in chores is more likely to result in direct time savings, whereas in leisure it primarily aims to enhance the quality of time spent rather than to reduce the time required. In mobility, time-saving "replace" applications that still require human presence coexist with collaborative applications, especially in trip planning.

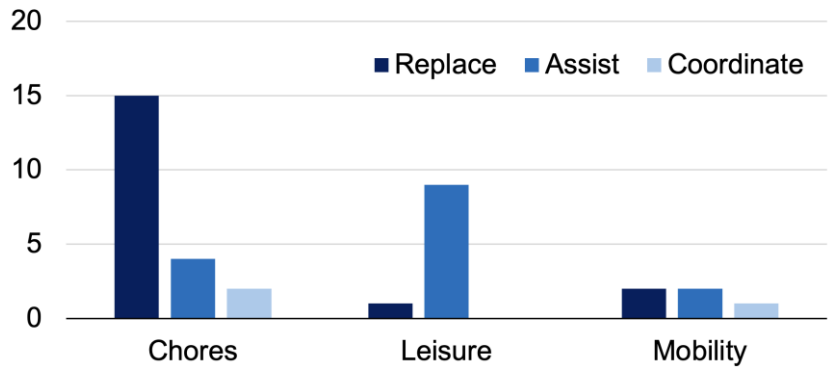


Figure 2. Number of automation applications by life domain (chores, leisure, mobility) and machine-human interaction (replace, assist, coordinate) based on the structured expert coding approach. Coding results by application are provided in Table 6 in the Appendix.

5.3 Results of the energy effect coding of real-world applications

The net energy impact of automation depends on shifts in both the energy intensity and duration of the automated activity, as well as its substitute activities. In the following, we first show the results of the expert coding of changes in the energy intensity of the automated activity, followed by potential effects on substitute activities.

Figure 3 shows the likely effects of the applications on the direct energy-intensity (energy use per unit of time) of the automated activity. We could not distinctly classify all applications, as energy comparisons with conventional activities were often highly context-dependent. Still, the results show a pattern. In chores, numerous applications can be identified that both increase and decrease direct energy intensity. For example, intelligent heating and lighting systems are often designed to reduce energy consumption, while robotic cleaning devices typically operate on limited battery capacities (Hou et al., 2018; IEA, 2025). However, increases in chore energy intensity also occur, since many activities only get electrified through automation, such as food dispensing, watering plants, or automatically operating door locks. In mobility, energy-

saving applications dominate as self-driving technology and trip planners typically increase fuel efficiency or suggest fuel efficient routes. In contrast, in the leisure sector, most applications tend to increase direct energy intensity, and we could find only one leisure application that likely saves energy (health trackers, but only if health data was collected with conventional health monitoring devices before). This is because automation in leisure activities is often designed to enhance functionality and user experience, today increasingly through AI, which adds to energy use.

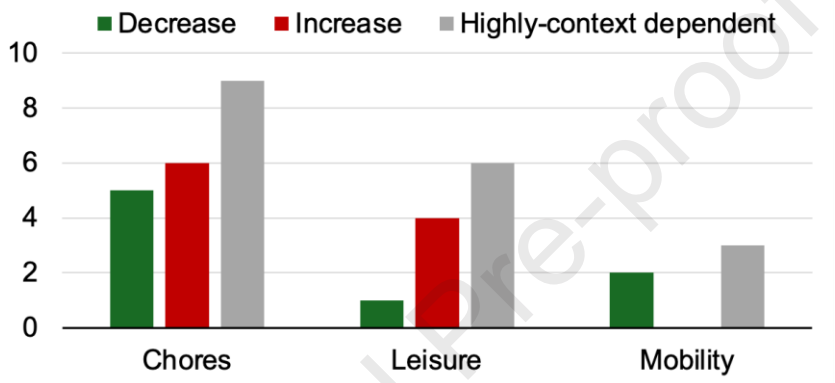


Figure 3. Number of automation applications by life domain (chores, leisure, mobility) and impact on the direct energy intensity of the automated activity. The underlying application classification is provided in Table 7 in the Appendix.

For substitute activities, energy effects vary greatly depending on the type of activity. Figure 4 illustrates the direct energy intensity of typical activities based on a study conducted in France in 2009-2011. While the data are dated, we have not identified a more recent study offering a similarly systematic comparison of direct energy intensities. Broad differences between activities, such as motorized transport and home-based leisure, remain informative as the relative difference across activities tends to change only very slowly over time; however, neither the absolute intensities nor their precise ranking can be assumed to represent current conditions.

The data show that activities involving motorized transport are highly energy intensive. On average, chores consume more energy than home-based leisure activities. Only out-of-home leisure that involves transport or larger infrastructures is energy-intensive. Thus, if automation decreases the time spent on chores and increases leisure time, there is, in principle, potential for energy savings. However, as discussed in the previous section, automation can also make leisure activities more energy intensive. Also, transferring human time from chores to leisure through automation does not eliminate chores energy use; it simply shifts the energy use from human effort to machines performing those tasks. Thus, the net energy impact of automation depends on the ratio between the energy intensity and time savings of the automated activity and those of the activities that replace it, which is highly context dependent as illustrated in the following case study.

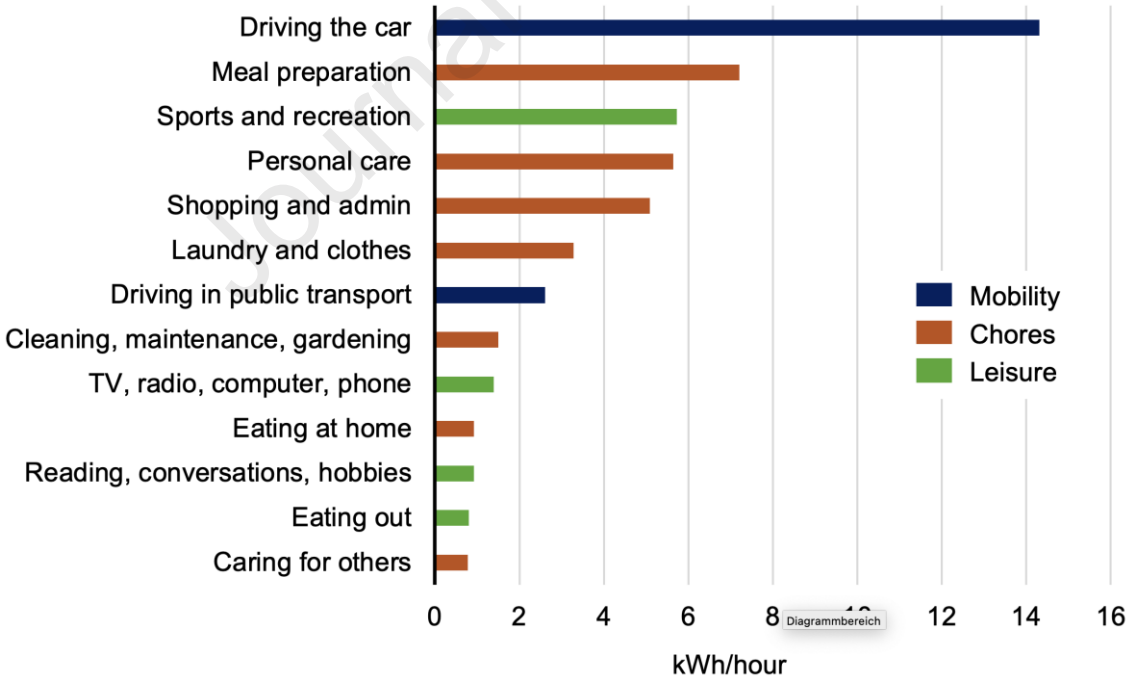


Figure 4. Direct energy use of activities in France 2009-2011 according to De Lauretis et al. (2017) and aggregated by Bieser et al. (2022).

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6. Illustrative case study of robot vacuum cleaners

Here we use robot vacuum cleaners as an example to examine the net energy impacts of automation by considering both changes in time use and direct energy intensity.

We estimate that an average manual vacuum cleaner has a power draw between 200 and 1,200 watts (median 700 watts) and is used for 35 minutes per week (Bayliss, 2024), resulting in a weekly electricity consumption of 0.41 kWh. In comparison, robot vacuum cleaners typically have a much lower power draw, averaging around 20 to 50 watts (median 35 watts, Ecovacs, 2018). However, they are typically used for longer periods (Vrain et al., 2026). According to recommendations from one of the leading manufacturers, robot vacuums should be used two to four times a week, with each session lasting approximately 30 minutes per room (Ecovacs, 2024). For a three-room apartment, this translates to a weekly cleaning time of 270 minutes and a total electricity consumption of 0.16 kWh. As a result, the robot vacuum saves about 0.25 kWh of electricity per week, despite its longer operating time. It is important to note, though, that the suction power of a robot vacuum is lower (Vaussard et al., 2014), meaning an extended runtime may be necessary to achieve a similar level of cleanliness as a manual vacuum cleaner.

At the same time, individuals save up to 35 minutes per week on cleaning, minus the time needed for preparing and following up on robot cleaning. Below, we illustrate how much of this saved time must be reallocated to other activities to fully offset the energy savings achieved through vacuum automation. To do this, we draw on data from the time- and energy-use studies in Figure 4. Figure 5, for example, illustrates if just one minute of the saved time is spent driving a car (e.g., for extra shopping or leisure trips), the energy savings achieved through robot vacuum cleaners are effectively negated. If the time is used for additional meal preparation, it takes about 2

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minutes to offset the savings, and for personal care activities (e.g., showering), around 3 minutes. When the time is spent on additional ICT use (e.g., watching TV or using a computer), the offset time rises to 11 minutes, and for reading or other hobbies, to 16 minutes, as these activities tend to be much more energy efficient.

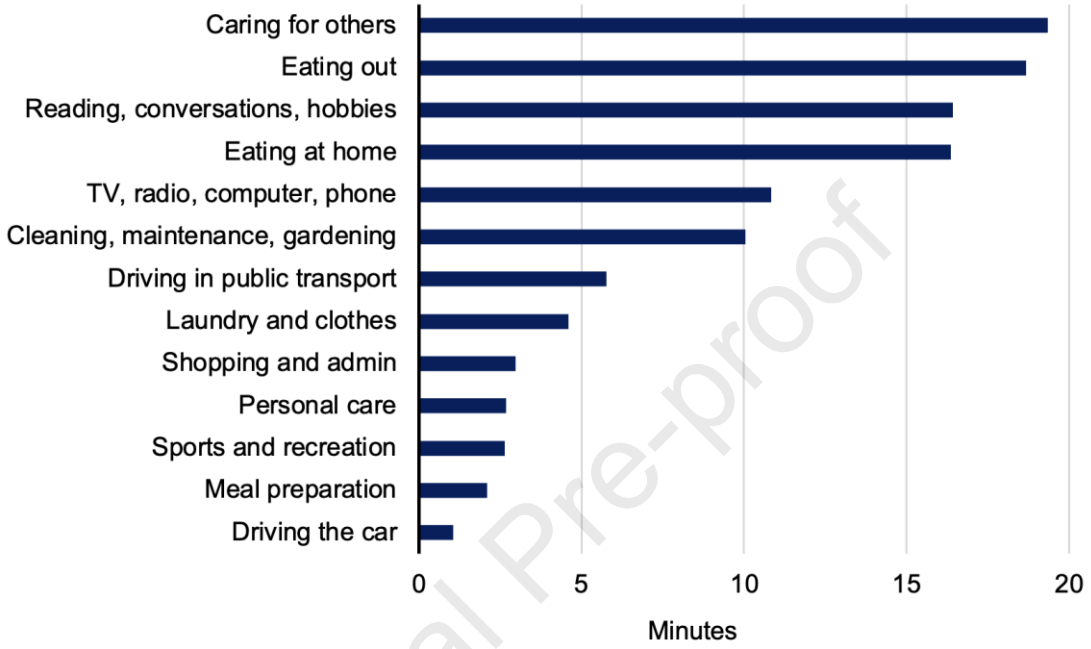


Figure 5. The number of minutes needed to be spent on other activities to fully offset the energy savings from robot vacuum cleaners, based on the scenario described above. The underlying activity-specific energy intensities are based on data from 2009–2011. Therefore, the figure primarily illustrates broad differences across activities rather than current empirical thresholds.

These numbers must be interpreted with care as they are based on context-dependent results from studies conducted in different countries and time horizons, with partially different system boundaries. However, all used data reflect direct energy use of activities and thus are suitable to demonstrate that the choice of substitute activities plays a key role in determining the net energy effects. In the case of robot vacuum cleaners, it is possible that a time rebound effect of over 100% will occur, resulting in

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an overall increase in energy consumption, as vacuum cleaning is less energy-intensive than many other activities. This result supports the findings by Mizobuchi and Yamagami (2024), who showed that while robotic vacuum cleaners may reduce energy use for vacuuming, they can lead to reallocation of time to activities that offset the energy savings from the automation device.

7. Discussion

In the following, we discuss the broader patterns in how automation affects time use, particularly the consequences for energy use across private life domains revealed by the analysis.

7.1 Time-use effects of automation

This study shows that time-use effects of applications differ across life domains. In chores (and partly mobility), automation often replaces human effort directly, making time savings more visible and immediate. In leisure, by contrast, automation more often supports human–machine collaboration, extending functionality and enabling users to do more, rather than simply reducing effort.

However, as noted in the literature review, even when time savings are achieved, rebound effects can occur. In chores, automation can reduce the time required for routine tasks, but these savings may be offset if expectations or activity levels increase (Carr, 2013; Cowan, 2023). Similar dynamics are well established in mobility. Faster and more convenient transport systems often result in longer distances rather than less travel overall. For instance, the constant travel time budget hypothesis suggests that people consistently spend about 1–1.3 hours per day traveling, regardless of the available transport technology, since faster modes allow them to reach more distant destinations (Ahmed & Stopher, 2014). This suggests that automation should not be

understood simply as a tool for saving time, but as a force that reshapes how time is allocated and what levels of convenience and performance become normal.

7.2 Energy effects

Our analysis of real-world applications identified several mechanisms through which automation can either increase or decrease the energy intensity of activities. First, automation can lower direct energy intensity by improving operational efficiency. This was particularly evident in chore and mobility applications, where machine control may outperform human control, for example through more fuel-efficient driving in self-driving vehicles or reduced unnecessary heating through smart thermostats. Battery-based design can also promote energy efficiency, as seen in robot vacuum cleaners with lower power demands than conventional manual vacuums. At the same time, automation can raise direct energy use by requiring additional sensors, motors, (AI-based) data processing, and new functionalities. These contrasting mechanisms are summarized in Table 3.

Impact on energy intensity	**Name**	**Description**	**Example**
Reducing	Elimination of fixed power supply	Elimination of a fixed power supply for mobile use, making it essential to prioritize energy-efficient design due to the limited battery capacity.	Robot vacuum cleaners having lower power draws than manual vacuums
	Algorithmic-driven efficiency	Algorithmic control of a process can increase energy efficiency compared to human control.	Self-driving vehicles accelerating more smoothly than human drivers
	Context-based decision making	Automated systems take contextual information into account, enabling them to optimize energy consumption proactively and based on actual needs	Intelligent heating systems adjusting energy use to weather and occupancy
Increasing	Energy-consuming technology	Automation often demands extra energy for sensors and actuators. Tasks that did not consume energy may become reliant on energy-consuming devices through automation.	Sensors and motors for robotic window cleaners
	Data growth	Automation increases data transmission and (AI-based) processing over end-user devices, networks and data centres.	Self-driving vehicles causing substantial data transfer and processing

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	New functionalities	Automation often adds functionalities beyond those of manual operation, which can lead to increased energy consumption.	Scheduling functions for automated coffee machines or watering systems

Table 3. Identified mechanisms increasing and decreasing the energy intensity of the automated activity.

Generally, the number of connected digital devices per capita continues to increase (United Nations, 2024). The new possibilities provided by automation can further nurture this trend and contribute to an electrification and materialization of leisure and chore activities. Already in 2011, Aall (2011) observed a similar trend, calling it the "materialization of leisure." It describes how the growing dependence on equipment for leisure has intensified environmental impacts, such as the increased use of specialized clothing for outdoor recreation. Digitally-enabled automation may now produce analogous effects across various private life activities. This materialization can compound increases in operational energy use as additional devices, sensors and supporting infrastructure also require energy for material extraction, manufacture, transport and end-of-life treatment. These embodied requirements were out of scope in our assessment but can increase even total energy use even if devices become more efficient during use, particularly when automation adds equipment rather than replacing existing products or encourages more frequent replacement. Conversely, longer lifetimes and the use of existing hardware may limit additional embodied demand.

Beyond the energy intensities of single activities, the broader consequences of automation depend on how it changes time and thus energy use for other activities. If automation reduces time spent on one activity, that time is shifted to other activities, whose energy implications may be lower or higher. This is highly context dependent. As mentioned in the literature review, research suggests that the sharp increase in ICT use has led people to have more ICT-based hobbies (streaming, computer use) and

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therefore spend more time at home and less traveling, one of the most energy-hungry activities if motorized transport means are used (Sekar et al., 2018). In other cases, automation may make already energy-intensive activities more attractive, particularly private car travel through self-driving technologies (Coroamă & Mattern, 2019; Hörl et al., 2019).

Finally, without automation, energy consumption linked to time use was somewhat constrained by the number of activities that could be carried out at the same time. Automation removes some of these constraints by allowing multiple activities to run simultaneously without human attention, causing energy use to accumulate across devices in ways that were previously restricted by human attention and presence.

7.3 Limitations

This study also has important limitations. First, we did not assess indirect energy impacts, such as those linked to increased device purchases and production, although the materialization of activities suggests that such effects may be significant. Second, we did not address broader systemic changes in time-use patterns that emerge when multiple automation applications interact. Third, results of expert coding are shaped by the researchers' prior knowledge and theoretical orientation, and do not include an external validation that the classifications correspond to observed user behaviour or energy outcomes. Therefore, we provide explanations of our assessments in Appendix Tables 6 and 7 so readers can assess our judgments. Also, the impacts identified here are context dependent and shaped by specific application functionalities and user practices that are continuously evolving due to rapid advancements in automation. The value of the analysis therefore lies less in predicting the exact effects of individual applications and more in identifying broader mechanisms and patterns that can guide future research and policy. Future studies could validate the time-use classifications

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through user surveys and longitudinal time-use diaries that record preparation, supervision, interaction and simultaneous activities before and after adoption. These records could be linked to device-level electricity measurements and household smart-meter data to test the coded direction of direct energy-intensity changes.

8. Conclusion and future work

The number and variety of automation applications are growing rapidly, reshaping how people use their time and with potentially important consequences for energy use. Because empirical evidence on the time and energy impacts of this wide range of applications is still lacking and difficult to generate, we conducted a conceptual study based on expert coding to identify the main opportunities and risks of automation for energy-efficient living.

The main opportunities lie in reducing the energy intensity of activities through more efficient device design and energy-optimized algorithmic control, and in shifting time toward lower-energy activities by making them more attractive and reducing engagement in high-energy ones. The main risks are the materialization and electrification of everyday life through more connected devices and data use, the accumulation of energy demand through simultaneous automated activities, and rebound effects when time savings lead to more frequent use.

Our findings suggest that as automation expands in private life, strategies are needed to ensure that it supports, rather than undermines, sustainable lifestyles. Otherwise, automation may increase reliance on energy-intensive devices and raise overall energy use. In this context, the digital sufficiency approach by Santarius et al., (2022) offers a useful starting point by combining measures to reduce ICT-related impacts with efforts to encourage more sustainable patterns of use.

Based on our analysis, we recommend four priorities for future research:

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- First, updating our calculations using recent, geographically relevant data on activity-specific energy intensities and empirical evidence on behavioural changes resulting from automation adoption.
- Second, examining how digital automation can be systematically used to lower the energy intensity of different activities.
- Third, exploring how automation can be designed to encourage energy-saving behaviour, for example through built-in nudges.
- Fourth, developing future lifestyle scenarios for an increasingly automated world that consider the combined effects of multiple applications on time use, energy demand, and possible trade-offs with social and economic sustainability to inform policy development.

Despite the limited empirical evidence, several recommendations for practitioners can already be made. Policy and design should steer automation toward energy-efficient device design, low-energy defaults, and algorithmic control that reduces the energy intensity of activities, while also limiting unnecessary device proliferation, standby consumption, and other forms of everyday electrification. Products and services should also be assessed not only for their direct efficiency gains, but also for rebound risks, such as more frequent use and the simultaneous operation of multiple devices. The coding provides suitable starting points for these measures. For "replace"-applications in chores, designers can preserve the identified efficiency opportunities through low-power operation, limits on unnecessary repeat cycles and automatic shutdown. For "assist"-applications, particularly leisure tools that increase direct energy use or have context-dependent effects, additional demand could be limited by making energy-intensive features optional, allowing users to set session limits, and avoiding defaults designed to maximize engagement. For "coordinate"-applications,

such as grocery delivery and ride-hailing, assessments should account for energy use shifted from users to service providers and examine how service providers can reduce overall energy demand, e.g. by consolidating deliveries or avoiding duplicate user and provider trips. Across categories, feedback on total energy use and concurrent device operation could help users identify accumulation that per-device efficiency indicators overlook.

Overall, this study highlights that the energy implications of automation depend not only on technical efficiency, but also on how technologies shape practices, routines, and expectations in daily life.

Acknowledgements

[Removed to ensure anonymity during the review process.]

Author contributions

[Author 1]: Conceptualization, data curation, methodology, investigation, formal analysis, writing – original draft, writing – review and editing. [Author 2]: Data curation, investigation, formal analysis, writing – original draft, writing – review and editing

Data availability statement

The authors confirm that the data supporting the findings of this study are available within the article and its appendix.

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Appendix

Coding questions for time-use effects

Table 4 shows the final coding questions, the answer options and the Cohen's Kappa reflecting intercoder agreement.

Category	Question	Answer options	Cohen's Kappa	Cohen's Kappa interpretation
Time-use: Role of machine	Does the application autonomously execute the full task after activation?	- Yes - No	0.83	Almost perfect agreement
	Does the application provide additional features that might encourage users to spend more time engaging with it?	- Yes - No	0.55	Moderate agreement
Time-use: Role of human	Are human activities required before most runs of the application (e.g., preparation or follow-up)?	- Yes - No	0.53	Moderate agreement
	Is repeated human input necessary during the execution of the task by the machine?	- Yes - No	0.83	Almost perfect agreement
	Does the machine require human supervision while it is executing the task?	- Yes - No	n/a*	Perfect agreement*
	Would a person multitask while the machine executes the task, or focus on it (e.g. waiting for result to give feedback or approve)?	- Focus - Multitask - Context-dependent	0.46	Moderate agreement
Energy-intensity	Does the automation application increase or decrease the direct energy intensity of the activity, or is the effect highly context-dependent and not clearly classifiable?	- Increase - Decrease - Context-dependent	0.53	Moderate agreement

Table 4. Coding questions used for time-use and energy-intensity effects and Cohen's Kappa per question. *Cohen's Kappa cannot be calculated in case of perfect agreement. For the average calculation this value is considered to be 1.0.

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Decision rules

Table 5 shows the decision rules applied to assign each application into a time-use effect category based on the coding results.

Question	**Answers allowed in REPLACE category**	**Answers allowed in ASSIST category**	**Answers allowed in COORDINATE category**
Does the application autonomously execute the full task after activation?	Yes	No	Yes/No
Is repeated human input necessary during the execution of the task by the machine?	No	Yes	No
Does the application provide additional features that might encourage users to spend more time engaging with it?	No	Yes/No	Yes/No
Are human activities required before most runs of the application (e.g., preparation or follow-up)?	Yes/No	Yes/No	Yes/No
Does the machine require human supervision while it is executing the task?	Yes/No	Yes/No	Yes/No
Would a person multitask while the machine executes the task, or focus on it (e.g. waiting for result to give feedback or approve)?	Mulitask/context dependent	Mulitask/focus/ context dependent	Mulitask/focus/ context dependent

Table 5. Decision rules.

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Time-use effects coding results

Table 6 shows the time-use effect coding results by application.

#	Category	Activity	End goal of the activity	Execution-Stage Automation Example	Example	Role of machine			Role of human			Brief justification
						Does the application autonomously execute the full task after activation?	Does the application provide additional features that might encourage users to spend more time engaging with it?	Are human activities required before most runs of the application (e.g., preparation or follow-up)?	Is repeated human input necessary during the execution of the task by the machine?	Does the machine require human supervision while it is executing the task?	Would a person multitask while the machine executes the task, or focus on it (e.g. waiting for result to give feedback or approve)?	
1	Leisure	Message responding	The message is sent	AI-writing assistants	LinkedIn automated responses	No	Yes	No	Yes	No	Focus	Humans interact with tool to create final answer
2	Leisure	Blog writing	An article is finalized and published	AI text generators	ChatGPT auto-write	No	Yes	No	Yes	No	Focus	Humans interact with tool to create final answer
3	Leisure	Browsing news websites	One is updated with the latest news	News aggregators	Yahoo News	No	Yes	No	Yes	No	Focus	Human browses suggestions and interacts with articles
4	Leisure	Finding reading materials	The next book to read is selected	Content recomm. systems	Amazon book recom.	No	Yes	No	Yes	No	Focus	Human browses suggestions and makes selection
5	Leisure	Selecting music for listening	Listening to music	Smart playlists	Spotify autoplay	Yes	Yes	No	No	No	Multitask	Tool automatically selects and plays songs
6	Leisure	Selecting film/TV episode	The next movie to watch is selected	Smart watchlist	Netflix autoplay	No	Yes	No	Yes	No	Focus	Human browses suggestions and makes selection
7	Leisure	Planning training programs	The training plan is finalized and ready to implement	AI training assistants	Freeletics Coach	No	Yes	No	Yes	No	Focus	Human analyses suggestions and revises plan with the tool
8	Leisure	Conversational language learning	One's language skills are improved	AI language learning chatbot	Duolingo Max	No	Yes	No	Yes	No	Focus	Human interacts with the tool to improve language skills
9	Leisure	Artmaking	An art piece is finalized and ready for publication	AI art generators	DALL·E	No	Yes	No	Yes	No	Focus	Human collaborates with tool to create final art piece
10	Leisure	Image/video editing	A video is edited and ready for publication	AI video editors	RunwayML	No	Yes	No	Yes	No	Focus	Human collaborates with tool to create final image/video

11	Leisure	Health checks	Health data is collected	Fitness and health trackers	Fitbit heart monitoring	Yes	No	No	No	No	Multitask	Tool automatically collects data
12	Chores	Floor cleaning	The floor is clean	Robot vacuum cleaners	iRobot Roomba	Yes	No	Yes	No	No	Multitask	Robot cleans automatically but humans need to empty dustbins
13	Chores	Clothes ironing	The clothes are ironed	Automatic ironing mach.	Scanovus	No	No	Yes	Yes	No	Context-dependent	Human sorts, loads, and unloads each clothing item separately
14	Chores	Window cleaning	The windows are clean	Robotic window cleaners	Ecovac Winbot	Yes	No	Yes	No	No	Multitask	Robot cleans auton. but humans need to set-it up before each run
15	Chores	Paying bills	The bills are paid	Autom. bill payment sys.	Standing order	Yes	No	No	No	No	Multitask	After initial set-up orders are executed autonomously
16	Chores	Financial investing	The investment decision is taken and executed	Robo-advisors (with human approval)	Betterment	No	Yes	No	Yes	No	Focus	Human analyses suggestions, potentially revises it and approves
17	Chores	Feeding pets	The pet is fed	Automated food dispenser	Petlibro	Yes	No	Yes	No	No	Multitask	Feeding occurs autonomously but human needs to refill food
18	Chores	Playing with pets	The pet is entertained	Robot pet companion	Oro	Yes	No	No	No	No	Multitask	Robot plays with pet autonomously after activation
19	Chores	Cutting the lawn	The lawns are mowed	Robot lawnmower	Robomow	Yes	No	Yes	No	No	Multitask	Robot cleans automatically but humans need to empty tray
20	Chores	Garden watering	The plants continuously have sufficient water	Automated watering syst.	Gardena	Yes	No	No	No	No	Multitask	Watering systems is connected to water supply and runs auton.
21	Chores	Shopping in general	The out-of-stock goods are ordered	Autom. restocking service	Amazon Dash	Yes	No	No	No	No	Multitask	Restocking service orders autonomously
22	Chores	Discovering products	The products are selected and bought	Product recommender sys.	Amazon	No	Yes	No	Yes	No	Focus	Human checks and revises suggestions and approves order
23	Chores	Paying for products	The bill is paid	Just-walk-out technology	Amazon Go	Yes	No	No	No	No	Context-dependent	After initial registration payments are executed autonomously
24	Chores	Grocery shopping	Groceries are delivered at the door	Grocery delivery apps	Ocado with pre-filled basket	No	No	No	Yes	No	Multitask	Tool delegates shopping to a service provider
25	Chores	Meal planning	The meals for the next week are planned and ordered	Meal delivery services (subscription-based)	HelloFresh	Yes	No	No	No	No	Multitask	Tool delegates planning and preparation to a service provider
26	Chores	Locking doors and windows	The doors are locked or open	Smart locks (full presence-based automation)	VW Keyless Entry	Yes	No	No	No	No	Context-dependent	Locks operate autonomously based on key presence

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27	Chores	Switching lights	The lights are on/off as necessary	Smart lighting systems (full automation)	Philips Hue	Yes	No	No	No	No	Multitask	Lighting system operates autonomously based on sensors or schedules
28	Chores	Food preparation	The meal is cooked and ready to eat	Autom. cooking appliances	Thermomix	No	Yes	Yes	Yes	No	Context-dependent	Human needs to prepare foods, fill and take out foodstuffs from device
29	Chores	Brewing coffee	The coffee is ready to drink when desired	Automated coffee machines (with scheduling)	Jura Z10	Yes	No	Yes	No	No	Multitask	Brewing is executed autonomously; refilling is only occasionally needed
30	Chores	Managing indoor climate	The room temperature is always comfortable	Smart thermostats (without overwrite)	Nest	Yes	No	No	No	No	Multitask	Temperature regulation runs autonomously if there is no human overwrite
31	Chores	Air purification	The room climate is good	Automated air purifiers	Dyson Pure Cool	Yes	No	No	No	No	Multitask	Purification runs autonomously if there is no human overwrite
32	Mobility	Driving	One reaches their destination safely	Self-driving cars (level 4 automation)	Tesla Autopilot	Yes	No	No	No	Yes	Context-dependent	Driving is done auton. unless human intervenes, but supervision is required
33	Mobility	Collecting goods	Ordered goods arrive at the home	Delivery robots	Starship robots	Yes	No	No	No	No	Multitask	Robots deliver goods autonomously
34	Mobility	Multimodal trip planning	The connection is decided upon	Mobility-as-a-Serv. apps	Citymapper	No	No	No	Yes	No	Focus	Human evaluates trip suggestion and takes final decisions
35	Mobility	Ride-hailing	One reaches their destination with a ride hailing service	Ride-hailing services	Uber	No	No	Yes	Yes	No	Multitask	Tool delegates transport to a service provider
36	Mobility	Trip planning	The trip plan is finalized and ready to be implemented	Smart trip planners	Google Trips	No	Yes	No	Yes	No	Focus	Human analyses suggestions and revises plan with the tool

Table 6. Time-use effects coding results.

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Energy-intensity effects coding results

Table 7 shows the energy-intensity effects coding results by application.

#	Category	Activity	End goal of the activity	Execution-Stage Automation Example	Example	Does the automation application increase or decrease the direct energy intensity of the activity, or is the effect highly context-dependent and not clearly classifiable? This question is only about the energy per time unit, not the time spent on the activity.	Brief justification
1	Leisure	Message responding	The message is sent	AI-writing assistants	LinkedIn automated responses	Increase	Additional energy-consuming AI features
2	Leisure	Blog writing	An article is finalized and published	AI text generators	ChatGPT auto-write	Increase	Additional energy-consuming AI features
3	Leisure	Browsing news websites	One is updated with the latest news	News aggregators	Yahoo News	Highly-context dependent	Algorithmic processing adds energy but replaces manual browsing
4	Leisure	Finding reading materials	The next book to read is selected	Content recomm. systems	Amazon book recom.	Highly-context dependent	Algorithmic processing adds energy but may reduce browsing effort in shops
5	Leisure	Selecting music for listening	Listening to music	Smart playlists	Spotify autoplay	Highly-context dependent	Algorithmic processing adds energy but replaces manual searching
6	Leisure	Selecting film/TV episode	The next movie to watch is selected	Smart watchlist	Netflix autoplay	Highly-context dependent	Algorithmic processing adds energy but replaces manual searching
7	Leisure	Planning training programs	The training plan is finalized and ready to implement	AI training assistants	Freeletics Coach	Highly-context dependent	Algorithmic processing adds energy but replaces manual planning
8	Leisure	Conversational language learning	One's language skills are improved	AI language learning chatbot	Duolingo Max	Highly-context dependent	Depends on alternative learning scenario (e.g. learning app or classroom-based)
9	Leisure	Artmaking	An art piece is finalized and ready for publication	AI art generators	DALL·E	Increase	Additional energy-consuming AI features
10	Leisure	Image/video editing	A video is edited and ready for publication	AI video editors	RunwayML	Increase	Additional energy-consuming AI features
11	Leisure	Health checks	Health data is collected	Fitness and health trackers	Fitbit heart monitoring	Decrease	Wearables consume less energy than conventional health monitoring devices
12	Chores	Floor cleaning	The floor is clean	Robot vacuum cleaners	iRobot Roomba	Decrease	Robot vacuums normally have lower power draw than manual counterparts
13	Chores	Clothes ironing	The clothes are ironed	Automatic ironing mach.	Scanovus	Highly-context dependent	Highly device dependent

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14	Chores	Window cleaning	The windows are clean	Robotic window cleaners	Ecovac Winbot	Increase	Manual window cleaning requires no electricity
15	Chores	Paying bills	The bills are paid	Autom. bill payment sys.	Standing order	Decrease	Automatic initiation requires less energy than online banking
16	Chores	Financial investing	The investment decision is taken and executed	Robo-advisors (with human approval)	Betterment	Highly-context dependent	Algorithmic processing adds energy but replaces manual search and analysis
17	Chores	Feeding pets	The pet is fed	Automated food dispenser	Petlibro	Increase	Manual feeding requires no electricity
18	Chores	Playing with pets	The pet is entertained	Robot pet companion	Oro	Increase	Human playtime requires no electricity
19	Chores	Cutting the lawn	The lawns are mowed	Robot lawnmower	Robomow	Decrease	Automated lawn mowers normally have lower power draw than manual counterparts
20	Chores	Garden watering	The plants continuously have sufficient water	Automated watering syst.	Gardena	Highly-context dependent	Manual watering requires no electricity but humans may use more water
21	Chores	Shopping in general	The out-of-stock goods are ordered	Autom. restocking service	Amazon Dash	Highly-context dependent	Algorithmic processing adds energy but replaces manual online ordering
22	Chores	Discovering products	The products are selected and bought	Product recommender sys.	Amazon	Highly-context dependent	Algorithmic processing adds energy but replaces manual searching
23	Chores	Paying for products	The bill is paid	Just-walk-out technology	Amazon Go	Increase	Automated sensing infrastructure increases energy intensity of the payment process
24	Chores	Grocery shopping	Groceries are delivered at the door	Grocery delivery apps	Ocado with pre-filled basket	Decrease	Optimized delivery requires less energy than human (car) collection
25	Chores	Meal planning	The meals for the next week are planned and ordered	Meal delivery services (subscription-based)	HelloFresh	Highly-context dependent	Depends on alternative meal planning scenario
26	Chores	Locking doors and windows	The doors are locked or open	Smart locks (full presence-based automation)	VW Keyless Entry	Increase	Human locking does not require electricity
27	Chores	Switching lights	The lights are on/off as necessary	Smart lighting systems (full automation)	Philips Hue	Highly-context dependent	Automation system requires energy, may avoid unnecessary lighting or increase lighting through scheduling (e.g. during vacation)
28	Chores	Food preparation	The meal is cooked and ready to eat	Autom. cooking appliances	Thermomix	Highly-context dependent	Depends on alternative meals and cooking scenario
29	Chores	Brewing coffee	The coffee is ready to drink when desired	Automated coffee machines (with scheduling)	Jura Z10	Highly-context dependent	May have similar heating energy to manual machines but additional electronics involved.
30	Chores	Managing indoor climate	The room temperature is always comfortable	Smart thermostats (without overwrite)	Nest	Decrease	Automated optimisation often reduces heating and cooling energy relative to manual control if sensors detect occupancy
31	Chores	Air purification	The room climate is good	Automated air purifiers	Dyson Pure Cool	Increase	Manual purification requires no electricity

32	Mobility	Driving	One reaches their destination safely	Self-driving cars (level 4 automation)	Tesla Autopilot	Decrease	Automated vehicles drive more fuel efficient, despite additional computation
33	Mobility	Collecting goods	Ordered goods arrive at the home	Delivery robots	Starship robots	Decrease	Delivery robots are typically more fuel efficient than delivery trucks per parcel
34	Mobility	Multimodal trip planning	The connection is decided upon	Mobility-as-a-Serv. apps	Citymapper	Highly-context dependent	Depends on alternative planning scenario
35	Mobility	Ride-hailing	One reaches their destination with a ride hailing service	Ride-hailing services	Uber	Highly-context dependent	Depends on alternative travelling mode
36	Mobility	Trip planning	The trip plan is finalized and ready to be implemented	Smart trip planners	Google Trips	Highly-context dependent	Depends on alternative planning scenario

Table 7. Energy-intensity effects coding results.

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Declaration of interests

☐ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☒ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Emilie Vrain reports financial support was provided by European Research Council. Emilie Vrain reports financial support was provided by Research England. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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