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How home automation reshapes household time use and energy demand: Evidence from a mixed-methods longitudinal study

Emilie Vrain [a,*], Jan Bieser [b], Charlie Wilson [a,c]

[a] Environmental Change Institute, School of Geography and the Environment, University of Oxford, Oxford, UK
[b] Institute Public Sector Transformation, Business School, Bern University of Applied Sciences, Bern, Switzerland
[c] International Institute for Applied Systems Analysis (IIASA), Laxenburg, Vienna, Austria

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ABSTRACT

Domestic automation technologies are increasingly promoted as time- and energy-saving solutions, yet limited empirical evidence exists on how they are incorporated into everyday routines or how they influence household energy demand. Existing studies rarely examine real-world use over extended periods, leaving behavioural adaptations and indirect energy impacts underexplored. This paper addresses these gaps through a 15–18 month longitudinal mixed-methods experimental study of automation with 10 UK households, examining how the automation of floor cleaning reshapes time use and energy demand. Data were collected through repeated time-use diaries, smart-plug energy monitoring, app-based usage logs, participant reflections, and follow-up interviews. By integrating time-use analysis with typologies of indirect energy impacts, we quantify how automation alters when, how, how long and how often tasks are performed, frequently increasing total task duration and layering energy demand.

During the trial, floor-cleaning frequency increased on average by 32% and total cleaning duration by 189%, while occupants' manual cleaning time decreased by 45 %. Energy demand direct from the device declined in some households but increased in others due to more frequent device operation, reflecting diverse patterns of substitution, efficiency, and rebound effects. Longer-term follow-up showed use of the device became partially routine, with most households maintaining higher cleaning duration but reduced frequency relative to the trial period. The findings demonstrate that the energy outcomes of domestic automation are highly contingent on how technologies are embedded within household routines. The study highlights the need for context-responsive design, behavioural-aware energy policy, and further investigation of how digitally mediated routines shape domestic energy demand.

1. Introduction

Digital automation is increasingly embedded in everyday consumer technologies, offering promises of time savings, efficiency gains, and flexibility, benefits long associated with industrial automation [1]. The classic aim of automation has been to replace human manual control, planning and problem solving by automatic devices and computers [2]. In the home, automation technologies such as automatic vacuum cleaners (AVCs), smart thermostats, and smart lighting systems are now performing tasks once managed and conducted manually by household members. From a sustainability perspective, such technologies are often promoted as being energy efficient and claim to support low-carbon lifestyles through their ability to avoid unnecessary energy use and by enabling demand-side flexibility through shifting consumption to cheaper, less constrained periods [3,4]. However, the actual energy implications depend less on technical potential and more on how these technologies are adopted and used in real life [5,6].

However, we cannot assume that people will use automation in the way it was designed. Decades of sociotechnical research show that technologies are often adopted, adapted, or abandoned in ways that diverge from their intended function [7–9]. Studies of domestic technologies illustrate how social norms, household routines, and material contexts shape their uptake and use. For example, Cowan [10] documents how the washing machine reshaped expectations of cleanliness, while more recent work points to similar dynamics with smart appliances such as fridges [11]. Broader sociotechnical analyses likewise

* Corresponding author at: Environmental Change Institute, School of Geography and the Environment, University of Oxford, Oxford OX1 3QY, UK.
E-mail address: emilie.vrain@eci.ox.ac.uk (E. Vrain).

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highlight the role of routines and contexts in shaping adoption [8,12].

A time-use perspective provides a valuable lens for understanding how domestic automation reshapes household routines and energy demand. As time is a universally constrained resource, this approach makes it possible to examine how households allocate time across energy-consuming domestic and non-domestic activities. When applied to the study of domestic automation, it offers deeper insight into how digital technologies alter everyday behaviours and, in turn, influence overall energy demand [13,14]. Importantly, automation can affect not only the energy used directly to perform a task, but also have wider indirect consequences. These arise through behavioural and temporal shifts such as changes in when, how often or how long tasks are performed, or what new activities fill the time saved. As we show in this paper, such indirect impacts can either reinforce or undermine the energy savings anticipated from automation, and require a behavioural lens to be fully understood.

An underexplored distinction in existing research is between automation of the *planning* of an activity (e.g., scheduling, timing, coordination) and automation of the *execution* (the physical performance of the task). Many domestic activities consist of subtasks across planning and execution phases, and technologies often automate only some of these. For example, AVCs may automate the act of vacuuming but not the preparatory steps such as tidying up [15]. This partial automation enables users to adapt, work around or ignore certain functions, producing diverse routines with differing implications for time use, energy demand, and user agency. Positioning planning and execution automation as analytically separate promises a more precise understanding of where behavioural change emerges and how energy demand is redistributed. Our study explicitly operationalises this distinction to examine how each form of automation reshapes task timing, frequency and duration, and the resulting direct and indirect energy impacts.

We focus on AVCs as an illustrative case of domestic automation, as they clearly expose the behavioural and routine-based mechanisms through which automation affects time use and energy demand. Building on this case, we extend the literature and evidence in three important ways: 1) we collect and analyse longitudinal data through an experimental trial, capturing change in automation use, time allocation and energy use; 2) we utilise a wide range of mixed methods to provide rich insights into the underexplored behavioural and temporal dynamics of domestic automation; and 3) we focus on automation's direct, as well as indirect impacts on energy, offering novel evidence on household energy demand in an increasingly automated world.

The remainder of this paper is structured as follows. Section 2 reviews relevant literature on domestic automation and energy and time-use impacts. We then pinpoint important research gaps to derive our research questions. Section 3 presents our analytical framework which captures the relationship between use of automation, changes in time-use patterns, and the subsequent direct and indirect energy implications. We outline the mixed-methods approach used to track longitudinal changes and Section 4 presents key findings. Section 5 discusses these findings considering broader debates on automation and rebound effects, and Section 6 concludes with practical, policy and further research implications.

2. Literature review

2.1. Domestic automation and energy

Automation technologies originally focused on industrial and military contexts, developed to improve efficiency, productivity, safety, and control in structured environments [16,17]. From the 1950s onwards, domestic settings began to see early forms of automation, with appliances such as washing machines and dishwashers introduced to reduce physical labour and save time [18,19]. More recently, digital (internet-enabled) automation has rapidly extended further into domestic life, performing repetitive tasks such as cleaning, cooking, grocery shopping and climate control (Table 1). Many of these devices and services promote themselves not only as convenient and time saving, but also energy-efficient [20,21]. Several simulation studies substantiate such energy claims with Wilson et al. [22] and Mahmood et al. [23] providing an overview of such research. However, unlike industrial settings and simulation models, the domestic sphere presents a far more complex and socially embedded setting. Here, household routines and norms play a significant role in shaping how automation is adopted and used [7,10,24], raising questions about the energy-related consequences [5,25,26].

Energy research in the domestic automation field has primarily focused on energy-intensive activities like climate control, and studied technologies such as home energy management systems (HEMS), designed to monitor, control and optimise energy consumption in buildings. Studies tend to concentrate on energy consumption simulations [27,28] or focus on the early stages of adoption, examining consumers' adoption intentions e.g., [29,30], technology acceptance e.g., [31], and factors influencing uptake e.g., [32,33].

In contrast, few studies track actual users over time to capture domestic processes, routine integration and ongoing engagement e.g., [12,34,35]. Automation of routinised and repetitive chores like floor cleaning has received far less academic attention [36,37], likely due to the assumption that their energy impact is negligible.

Another line of research has investigated the energy impacts of

Table 1
Categorised overview of routinised, ubiquitous 'chore' activities in households with examples of automation and market available devices or services (adapted from Bieser and Vrain, forthcoming).

Category	Activity	Automation Example	Example
Managing home – hygiene, care, finances	Floor cleaning	Automatic vacuum cleaners	iRobot Roomba Combo
	Clothes ironing	Automatic ironing machine	Scanovus
	Window cleaning	Robotic window cleaners	Ecovac Winbot
	Paying bills	Automated bill payment systems	Direct debits
	Financial investing	Robo-advisors	Betterment
	Feeding pets	Automated food dispenser	Petlibro
	Playing with pets	Robotic pet companion	Oro
	Cutting the lawn	Robotic lawnmower	Robomow
	Garden watering	Automated watering system	Gardena
Retail – non-grocery	Shopping in general	Automated restocking delivery service	Amazon Dash
	Paying for products	Just-walk-out technology	Amazon Go
Retail – grocery	Grocery shopping	Grocery delivery apps	Ocado pre-filled basket
		Meal delivery services	HelloFresh auto prep
Managing home – lighting, devices, appliances	Locking doors/ windows	Smart locks	August Lock
	Switching lights	Smart lighting systems	Philips Hue
Managing home – cooking, dishwashing, other food related	Food preparation	Automated cooking machines	Thermomix
	Brewing coffee	Automated coffee machines	Nespresso Smart
Managing home – heating, cooling, hot water, + own energy	Managing indoor climate	Smart thermostats	Nest
	Air purification	Automated air purifiers	Dyson Pure Cool

digital technologies. Horner et al. [38] and Bremer et al. [39] summarise and conceptualise such effects, distinguishing direct and indirect impacts. *Direct energy* impacts refer to the energy use during the manufacture, operation, and disposal of digital devices and associated infrastructures (e.g., data centres and networks). Such impacts are relatively easy to measure. For example, measuring device-level metrics during operation, such as the electricity used to charge a robotic lawn mower which has been empirically measured at approximately 4.80 kWh per week [40]. However, the ubiquity and high frequency of routinised domestic activities may have significant cumulative effects when indirect impacts are considered.

Indirect energy impacts refer to the changes in energy consumption resulting from altered processes, systems, and behaviours. Such impacts are often further distinguished into substitution, efficiency, and rebound effects:

Substitution effects occur when digital products and services replace traditional options, e.g., the streaming of digital media reduces the need for physical production and distribution [41]. However, substitution can also lead to higher energy use (ibid). For instance, watering plants manually at home requires no electrical equipment, while automated irrigation systems depend on energy-consuming components like sensors and control units.

Efficiency (or optimisation) effects occur when ICT use reduces the use of another resource, such as energy [42]. For example, smart thermostats that adjust heating based on weather and occupancy, or automated cars that accelerate and brake more efficiently than human drivers and thereby save fuel [43]. In practice, efficiency and substitution effects frequently overlap, making it challenging to separate them clearly.

Rebound effects occur when reductions in energy demand from (digitally-enabled) efficiency or substitution trigger additional consumption, either of the same goods or service, or of others [44–46]. In time-use terms, due to the fixed 24 hour time budget on a given day, changes in time allocation to one activity triggers shifts in the duration, or the timing and sequence of other activities. If those activities are more energy intensive than the replaced activities, net energy use increases, implying a time rebound effect [47]. Drawing from the rebound typology in Lange et al. [48], they may manifest through automation as:

- higher task frequency (e.g. cleaning more often because it takes less time);
- energy of enabled parallel tasks (e.g., TV watching while AVC is cleaning);
- reallocation of saved time to higher-energy activities (e.g., baking).

Traditional rebound literature focuses on economic mechanisms such as income and substitution effects [46], but more recent work calls for attention to motivational, temporal, and psychological dimensions e.g., [49,50]. Guzzo et al. [50] highlight how efficiency gains can produce time-use rebounds, where saved time is spent on other energy-consuming activities. Mizobuchi & Hiroaki [51]'s randomised control trial found that participants with AVCs reallocated their time to other activities such as cleaning and cooking, and increased their household energy consumption.

Overall, indirect effects are driven by complex behavioural processes and are usually considered more relevant than direct effects from an energy perspective [52]. Given this, and the behavioural complexity of domestic settings, we are particularly interested in capturing not only direct, but also indirect impacts and do so through a time-use perspective.

2.2. Time-use effects of automation

One of automation's core value propositions is time saving. However, many scholars suggest there is a "substitution myth" regarding the belief that automation merely replaces human effort. Carr [25] and others e.g., [53,54] argue that automation often not only transforms the activity itself but also reshapes entire daily routines and time use in ways that are difficult to predict. Cowan [10] similarly highlights how historical domestic technologies, like washing machines led not to reduced housework and the saving of time but to higher expectations for cleanliness and more frequent laundering. This dynamic is not necessarily unique to legacy appliances and clothes washing; smart fridges that recommend and order groceries may reshape shopping frequency and food waste patterns [55,56], while automated lighting systems may shift expectations for comfort and ambiance [57]. In their framework on ICT's influence on activity planning and execution, Bieser & Hilty [14] break down an activity into aspects and identify how each is impacted by ICT, for example *activity scheduling* is impacted by the *relaxation of time constraints*. Despite the growing sophistication of domestic automation technologies, the literature rarely differentiates between planning automation and execution automation. However, this distinction is crucial as each type triggers different behavioural responses and time-use adaptations, yet empirical studies typically treat 'automation' as a single category.

Additional considerations of time use, relevant to the context of automation, are raised by Smetschka et al. [58] and Bergener & Santarius [59]. Smetschka et al. [58] stresses that time-use consequences vary by household characteristics such as income, size, and built environment. For instance, higher-income households may use freed time provided by automation for leisure activities involving greater energy use, while others may use it for unpaid care or work. Bergener & Santarius [59] point out how an individual's pace of life, feelings of being rushed, and the time constraints caused by other responsibilities such as work, care or chores can impact upon their time use. These nuances remain poorly captured in current automation research, along with a lack of understanding on how time-use patterns evolve over time after automation is introduced [60]. Initial use experienced during short trials [61] may differ from routinised use, and the novelty of automation may wear off over time, leading to behavioural drift or disuse [62,63]. Longitudinal studies are particularly important for capturing such trends.

2.3. Research gaps and research questions

Overall, existing literature points towards the following four research gaps: 1) limited empirical research on the energy impacts of automation in routine domestic tasks; (2) lack of longitudinal studies tracking users' behavioural adaptation or disuse over time; (3) insufficient attention to indirect impacts on energy use through a time-use perspective; and (4) limited empirical differentiation between planning automation and execution automation, despite evidence that each produces distinct behavioural and energy effects. In the study underlying this article, we address these research gaps by developing an integrated framework that links automation to time use and energy impacts. We use this framework as an analytical lens (see Section 3.1), applying it to the example automation application of AVCs and tackle the following research questions:

RQ1: How does the adoption of automation alter time-use patterns in the home over time?

RQ2: What are the direct and indirect energy implications of automation?

3. Methodology

3.1. Analytical framework linking automation, time and energy

To guide our analysis, we developed a framework that integrates Bieser & Hilty's [14] activity-aspects and time use framework with Horner et al.'s [38] typology of direct and indirect energy impacts. As shown in Table 2, our framework maps how aspects of automation planning and execution phases can generate direct energy impacts, as

Table 2

Mapping how automation of the planning and execution phase of an activity can have different direct and indirect impacts via time use on energy demand, drawing from Bieser and Hilty [14] and Horner et al. [38]. We only consider direct energy use during device operation and not for manufacturing or disposing it. AVC = automatic vacuum cleaner.

Bieser and Hilty				Horner et al.	
Phase	Activity Aspect	Time-use impacts of domestic automation	Potential time-use impacts Example of AVC	Direct energy impacts	Indirect energy impacts
Activity planning	1. Activity selection	Delegation of planning to digital systems requiring energy input	Delegating cleaning schedule to companion app	X (negligible)	–
	2. Activity scheduling	Shifts when activities are performed (e.g., alignment with off-peak times)	Scheduling cleaning overnight	–	Efficiency gains
	3. Planning horizon, duration and frequency	Changes in how far ahead tasks are scheduled, how often they are planned and task frequency	Ease of scheduling encourages more frequent cleaning	–	Potential efficiency; Potential same activity rebound
Activity execution	4. Associated activity manner	Alters frequency or type of associated activities	Tidying up before AVC runs	Depends on activity	Depends on activity
	5. Activity manner	Changes how an activity is performed (e.g. electrification of tasks)	Replacing manual sweeping with electric vacuuming	X	Substitution
	6. Activity duration	Tasks completed more quickly; time freed may be reallocated to other activities	AVC completes task quickly, user reallocated time to cooking	X	Efficiency gains; Other activity rebound
	7. Activity fragmentation	Tasks interrupted or partially completed due to system failures or user interventions	AVC stops mid-cycle and requires manual restart	n/a	n/a
	8. Parallelisation	Enables simultaneous performance of multiple activities	Watching TV while AVC is cleaning	–	Other activity rebound

well as indirect impacts mediated by time-use changes. We illustrate the different time-use impacts of automation through the example of AVCs, however the framework is applicable to a wide range of domestic automation technologies (for example those listed in Table 1). The framework highlights that assuming automation technologies save time and energy is overly simplistic, as the net energy impact depends on the combined magnitude of all individual impacts outlined in Table 2.

In principle, from a time-use perspective, automation introduces a second time budget: that of the machine or additional agent (e.g., a robot). Although the user is theoretically freed from the task, the robot's activity adds to overall time allocated to household processes. This, along with new associated activities to automation that the user performs (e.g., the set-up, preparation or supervision), also have consequences on overall time use and energy consumption.

Overall, we anticipate that the energy impacts of automation will depend less on the device's technical capabilities (direct energy impacts) and more on behavioural adaptations over time (indirect energy impacts), particularly the time-use dynamics outlined in Table 2. Although such automation-induced time rebound effects may appear subtle at the individual level, we argue they can cumulatively contribute to significant shifts in daily time-use patterns and overall household energy consumption when scaled.

3.2. General study set-up

We conducted a longitudinal mixed-methods experimental design study of automation in UK households, using AVCs as a case study. We followed households before, during, and one year after the introduction of AVCs and collected data on their usage patterns and experiences. By drawing on three phases, we move beyond assumptions of static, optimal or intended use, as well as short-term novelty effects of trials. Using data collected in all phases, we examine the behavioural consequences of domestic automation over time and how such changes impact household energy use.

We focus on AVCs and floor cleaning due to its ubiquity and routine nature, making it highly relevant for understanding everyday automation and it's impacts on time use and energy. Although AVCs require periodic user intervention and are not fully autonomous, these partial-automation characteristics are common across many domestic automation technologies marketed as "smart". Moreover, a wide range of consumer AVC technologies are commercially available that automate both the planning (e.g., scheduling when and where) and the execution (e.g. physical execution) aspects of floor cleaning. The market of AVCs automating floor cleaning has experienced rapid growth, reaching a value of $9.37 billion in 2024, and projected to expand further to $11.14 billion in 2025 [64]. The growth has been attributed to changing lifestyles and time constraints along with awareness and technological improvements [64].

3.3. Participating households

A sample of 10 households was selected from a broader three-year living lab infrastructure (2022–2025) based in and around Oxford, UK. As part of the living lab, participants continued living in their own homes under real-world conditions while trialling and reflecting on digital technologies. All 47 living lab households were invited to complete a short screening survey, and a total of 35 households responded. From these, we employed purposive sampling to select 10 households that provided variation in household composition (e.g., family type and size), prior levels of digital automation experience across daily life domains, and levels of activity intensity (e.g., cleaning frequency). Only households with no prior experience using AVCs were eligible to avoid bias from existing familiarity. The decision to recruit 10 households was shaped by the longitudinal, mixed-methods design and the availability of five AVC units, which required staggered deployment and intensive researcher engagement.

Selected households received detailed information and gave informed consent in accordance with ethical protocols. As an incentive, participants trialled an AVC with mopping capabilities for 30 days, with the opportunity to enter a prize draw to win one, and all got to keep a smart energy monitoring plug used during the study. This reward-based approach is commonly used in living lab research e.g., [65] and was used to support participant retention in a longitudinal design, minimise attrition, and compensate for the time burden of data collection activities.

3.4. Data collection

Data collection was conducted between June 2023 and November 2024. To capture behavioural time use and energy-related changes before and after the introduction of the device, a three-phase, multi-method data collection protocol was implemented (Fig. 1). As the study involved only five AVC units for 10 households, data collection was staggered across households. All fieldwork was conducted by a single researcher to ensure continuity, build trust and minimise attrition—a critical factor in longitudinal research. The full set of data collection

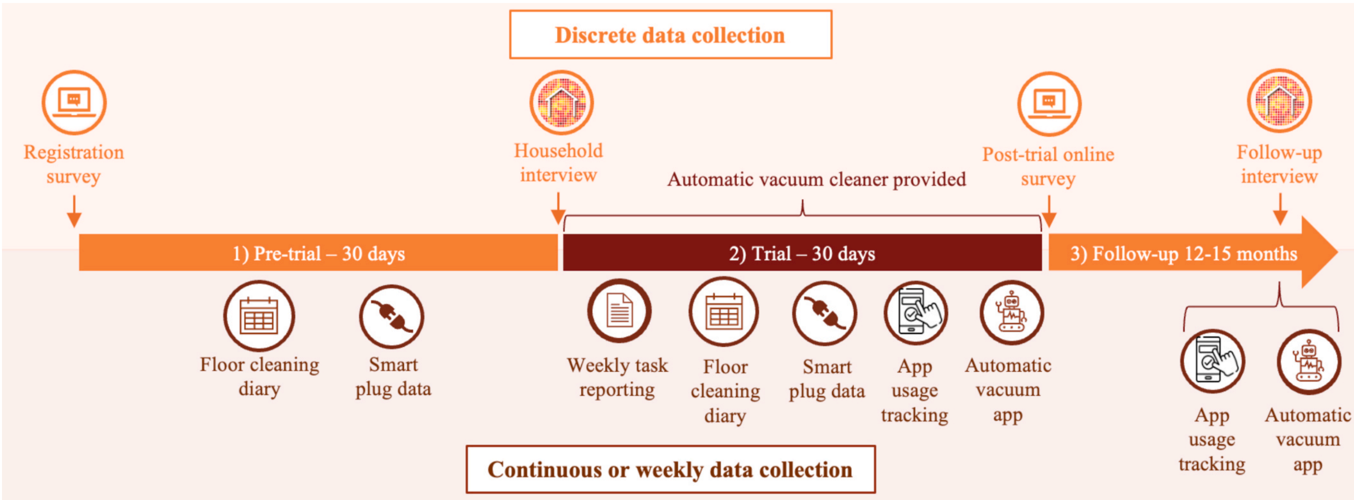

Fig. 1. Research protocol outlining the data collection timeline. The three phases are numbered, with discrete data collection placed above the timeline and continuous or weekly data collection placed below.

resources used in this study is provided in Data Availability.

Phase 1 – Pre-trial (30 days): To establish baseline data, each household was provided with 1) a smart energy monitoring plug (Kasa KP115) to measure electricity consumption in kWh of their existing VC and 2) a printed 'Mission Pack' which included a cleaning diary for visible placement (e.g., kitchen wall), which participants used to record floor-cleaning time-use data (i.e., frequency, timing, duration of instances) and contextual data (i.e., cleaned room(s), cleaning method, and responsible household member). Table A.1 in the Appendix outlines the different aspects of floor cleaning captured by the diary. A home-visit interview lasting between 60–90 minutes was conducted at the end of the pre-trial to verify diary entries, clarify cleaning routines, collect smart plug data and document general experience of automation use across 24 activities spanning 13 domains of daily life to provide additional contextual household insights.

Phase 2 – Trial (30 days): Following the interview, households received the AVC and were asked to install its companion app and to follow the manufacturer's instructions for setup. The AVC model provided to all households (Deebot N10) was a mid-range robotic vacuum with vacuuming and mopping functions, app-based mapping, zoned cleaning, and optional scheduling. It required manual emptying of the dust bin. These capabilities allowed for both planning and execution automation but still required some user input. Participants were given a brief safety and setup orientation on first use, as required by insurance protocols, but no guidance was provided on optimal usage, energy implications, or recommended routines. This was intentional to avoid influencing behaviour and to allow naturalistic integration of the device into household routines. App tracking was enabled to log time spent (minutes) using the companion app, and the smart plug was reassigned to the AVC's charging base. At the start of the trial, participants completed a short survey about their time allocation across work, chores and care, and measures of their pace of life [59].

Each week, participants completed tasks (Appendix, Table A.2) via instant messaging which tracked their AVC engagement and gathered rich qualitative reflections on their experiences and behaviours. These tasks included uploading screenshots of app usage data, filming first use reactions, providing qualitative reflections on time savings, and continuing the cleaning diary for any cleaning instances conducted by a household occupant. If summer travel disrupted continuity of data collection, the trial period was either extended or adjusted to ensure analysis represented 30 days.

Post-trial, all participants aged over 12 completed an online survey of closed and open-ended questions covering time use and behavioural change. The survey took on average 17 minutes to complete. A final home visit allowed the researcher to retrieve the AVC, collect smart plug and app data, and ensure completeness of weekly tasks. A prize draw randomly selected five households to retain an AVC post-trial.

Phase 3 – Follow-up (15–18 months later): Online interviews with all 10 households' adult participants captured long-term changes in routines, ongoing or discontinued device use, and the persistence of time and energy impacts. Interviews lasted between 20–30 minutes. Four of the five households that did not win the prize draw, purchased an AVC (the same model) resulting in nine households owning an AVC.

3.5. Mixed methods data analysis

A diverse range of data types was collected across the phases, combining objective measures (e.g., app-based logs, energy consumption from smart plugs), with subjective accounts (e.g., diaries, qualitative reflections, photos and surveys) (Fig. 2). Screenshots, written and audio entries were manually transcribed, and photos/videos were qualitatively described then organised by question or theme. All participant-generated materials (diaries, surveys, weekly reflections and interviews) were complete, with no missing entries. However, quantitative datasets varied in completeness across instruments. The AVC app logs, while reliably capturing total cleaning time and total cleaning occasions, provided detailed per-occasion records for only around two weeks for most households. Analyses therefore drew on the available detailed logs as these offered the richest behavioural insight. Smart-plug and diary data were more complete overall but varied slightly in duration across households (e.g., 27–35 diary days; 28 app-usage days; 27–32 smart-plug days).

To ensure comparability across households, all quantitative datasets were standardised to 7-days, with values divided by the number of recorded days to generate per-day rates and subsequently multiplied by seven. Although AVC units were rotated across households, all trials occurred within the same summer period, minimising seasonal variation.

3.5.1. Assessing uptake of automation

To investigate impacts of automation, it was first essential to assess actual uptake, as ownership or access does not guarantee usage. Using the framework presented in Table 2, we disaggregated the subtasks involved in floor-cleaning, mapped the automation potential of AVCs, and used a wide range of data sources to assess automation uptake by the households per floor cleaning sub-task (Appendix, Table A.3).

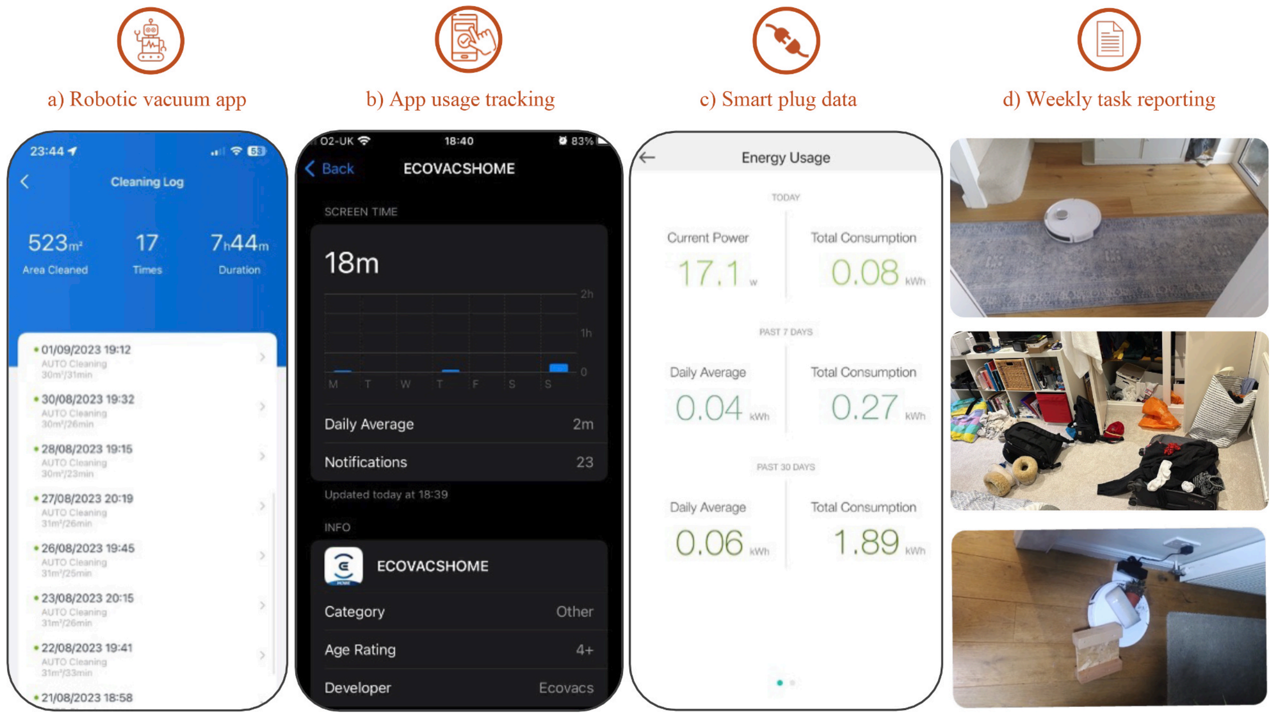

Fig. 2. Examples of data collected: a) time-use log from the automatic vacuum cleaner (AVC) companion app; b) app usage tracking; c) smart plug app energy log; d) participant-submitted photos reflecting automation experience.

3.5.2. Assessing changes in time-use patterns

Diary data from Phases 1 and 2 and app based data from Phase 2 (and Phase 3 where possible) were used to calculate shifts in timing, frequency and duration, and time spent on the new associated activity of companion app usage. As no diary was completed during the follow-up Phase 3, time-use changes were assessed from recall-based interviews covering the previous seven days, a period considered reasonable for reliable recall by participants [66].

Data across the phases were standardised to seven days to enable comparison. To deepen the understanding of shifts in time-use patterns, all qualitative responses were coded in NVivo v14 using a mixed inductive and deductive approach. Codes were developed around themes such as perceived time savings, multi-tasking, shifts in routines and disruptions. Results were used to triangulate patterns captured in diaries and monitored app behaviours.

3.5.3. Assessing energy impacts

Changes in direct energy use from the activity planning were deemed negligible as participants did not engage with the companion app in any substantial way. We focussed on calculating the energy use from the activity execution of floor cleaning through smart plug data (Phases 1 and 2). Where data was missing from six plugs in Phase 1 and one plug in Phase 2, additional calculations used manufacturer wattage specifications and diary-reported durations to estimate energy consumption. For Phase 3, established data from Phases 1 and 2 on device wattage per household were used in combination with the recall interview data on time spent floor cleaning. Comparative energy values were converted to kWh.

To assess the indirect energy impacts outlined in Table 2 we compared AVC time-use logs and occupant completed cleaning diaries from Phase 1 and 2 to identify shifts in when the task was performed (efficiency) and how often and for how long each method of cleaning (sweeping, mopping, VC and AVC) was used (substitution). Rebound effects were similarly captured through diary comparisons, with qualitative results to the question 'What activities have you been doing whilst the [AVC] is cleaning your floor?' coded by activity type to determine the potential indirect energy consumption of such parallel tasks enabled by automation.

4. Results

4.1. Automation uptake

4.1.1. Household composition and prior experience

First, we examine participating households' composition, prior automation experience, and observed automation uptake across the planning and execution aspects of floor cleaning during Phase 2 and 3 (Table 3). Although no clear relationship emerged between sustained uptake and household composition nor prior automation experience, the household with the highest prior experience (HH3) demonstrated the most integrated and enduring use of automation (across planning and execution). They purchased an additional AVC unit for upstairs and by Phase 3 had also adopted a robotic lawnmower. Such results suggest prior familiarity with other forms of automation may amplify positive reinforcement effects. However, other households with low or medium prior experience also adopted and engaged with the device, indicating that background familiarity is not a necessary condition for uptake.

Notably, four of the five households who did not win a device in the prize draw went on to purchase one. For instance, participant 5.1 reported *"we bought one even before the prize draw…the same model, same set-up"*. This suggests hands-on experience during the trial was a stronger determinant of perceived value and subsequent purchase compared to prior automation familiarity alone.

However, device ownership did not ensure sustained or comprehensive use of all automation potential. Patterns of partial automation were most common (Table 3). Many households used the AVC to automate execution of cleaning but retained manual control over when, where and how cleaning was initiated (the planning phase).

Reasons included a preference for spontaneity and a desire for flexibility. For example, participant 10.1 adopted a technique that bypassed the automation functions *"So I prefer to just get her [AVC] and I press the button and I shut the door and she just does her thing. And then she can't find*

Table 3
Summary of participating households' composition and home type, ordered by prior automation experience. Automation uptake is shown for the planning and execution of floor cleaning during Phase 2 and 3. Ownership of an automated vacuum cleaner (AVC) post-trial is also indicated.

ID				Automation uptake Phase 2			Automation uptake Phase 3	
	Household composition (age)	Home type (# bedrooms)	Prior automation experience [a]	Activity planning	Activity execution	Ownership post-trial	Activity planning	Activity execution
HH2	Couple (40 s), two children (<12)	Semi-detached (5)	Low	👤	💻	None	👤	👤
HH6	Couple (60 s)	Detached (3)	Low	👤	💻	Purchased 1	👤	👤
HH9	Single empty nester (50 s)	Terrace (3)	Low	👤	💻	Won 1	👤	💻
HH10	Single (40 s), one child (<12), one teenager	Semi-detached (3)	Low	👤	💻	Purchased 1	👤	💻
HH1	Couple (30 s), one toddler	Semi-detached (4)	Medium	👤	💻	Won 1	👤	👤
HH4	Couple (30 s)	Terrace (3)	Medium	👤	💻	Purchased 1	👤	💻
HH5	Couple (40 s), one teenager	Terrace (3)	Medium	💻	💻	Purchased 1	💻	💻
HH7	Couple (40 s), two children < 12	Semi-detached (4)	High	👤	💻	Won 1	👤	👤
HH8	Couple (30 s)	Semi-detached (3)	High	👤	💻	Won 1	👤	💻
HH3	Couple (50 s), son (20 s)	Detached (4)	High	💻	💻	Won 1 + purchased 1	💻	💻

💻 automation used, 👤 occupant maintained control.

[a] Household's adoption of automation across domains: low (none); medium (1–2 domains e.g., entertainment: smart speaker and home management devices: smart doorbell); high (>2 domains).

her base at the end. But I just pick her up and put her back". As for discontinuance, three households (HH1, 6 and 7) reported the device was not in use during Phase 3, due to situational disruptions, i.e., home renovations, moving house, or device malfunction. This highlights the sensitivity of automation uptake to broader domestic and material conditions, and the importance of context in sustaining technology use.

4.1.2. Time-use contexts

Time-use contexts such as time spent on paid work, household chores, care responsibilities and perceived pace of life were anticipated to shape automation uptake particularly among those responsible for cleaning. Results are provided in Supplementary Information (SI) Tables 1 and 2, and SI Fig. 1. Interpretation of the results reveals AVC usage during the trial is not linearly related to pace of life scores, total time burden, nor time spent specifically on chores (SI Fig. 1). In our sample, perceived time pressure, rather than actual time allocation, correlates more with delegation of cleaning to automation as the two individuals (participants 8.1 and 3.1) reporting 'always' feeling rushed had very high AVC usage. Overall, uptake and engagement varied widely across households, with hands-on trial experience emerging as a stronger determinant of sustained use than prior automation familiarity.

4.2. Impacts of automation on time-use patterns

For the remaining subsections, we map activity aspect(s) from the analytical framework in Table 2 to the subheadings. Each aspect links to both time-use and energy dimensions, but we present them where their implications are most directly observable, while noting overlaps.

4.2.1. Changes in when the activity is performed (aspect 2)

The introduction of automation had limited impact on shifting the scheduling of when cleaning occurred across households. In most cases, the timing of activity remained consistent with prior patterns, whether structured or ad hoc. Households with existing evening or daily cleaning patterns continued these rhythms into Phase 2, simply incorporating the AVC into established slots—typically later in the evening or layered with weekend routines. For households with more flexible or irregular pre-trial patterns, the use of automation similarly followed an ad hoc form, suggesting that automation did not significantly reconfigure temporal structures. Only three households demonstrated a noticeable shift: HH4 and HH5 moved away from evening cleaning, with HH5 being the only household to use the automation planning functionality, scheduling two cleans per day during Phase 2. This resulted in a narrowing of cleaning time window, which HH10 also experienced. Data is provided in SI Table 3.

4.2.2. Changes in frequency and duration of activity during trial (aspects 3 and 6)

The introduction of AVCs in Phase 2 increased cleaning frequency by an average of 32 % from a baseline of six occasions per week and increased total floor cleaning duration by 189 % from a baseline of 52 minutes per week (SI Fig. 2). However, occupant time spent cleaning dropped by 45 % (equivalent to an average reduction of 24 minutes per week). In eight of the ten households, the AVC undertook the majority of cleaning, often accounting for over 90 % of cleaning time (SI Table 4 e.g., HH3: 92 %; HH5: 99 %).

Fig. 3a shows results for floor cleaning completed by occupants and

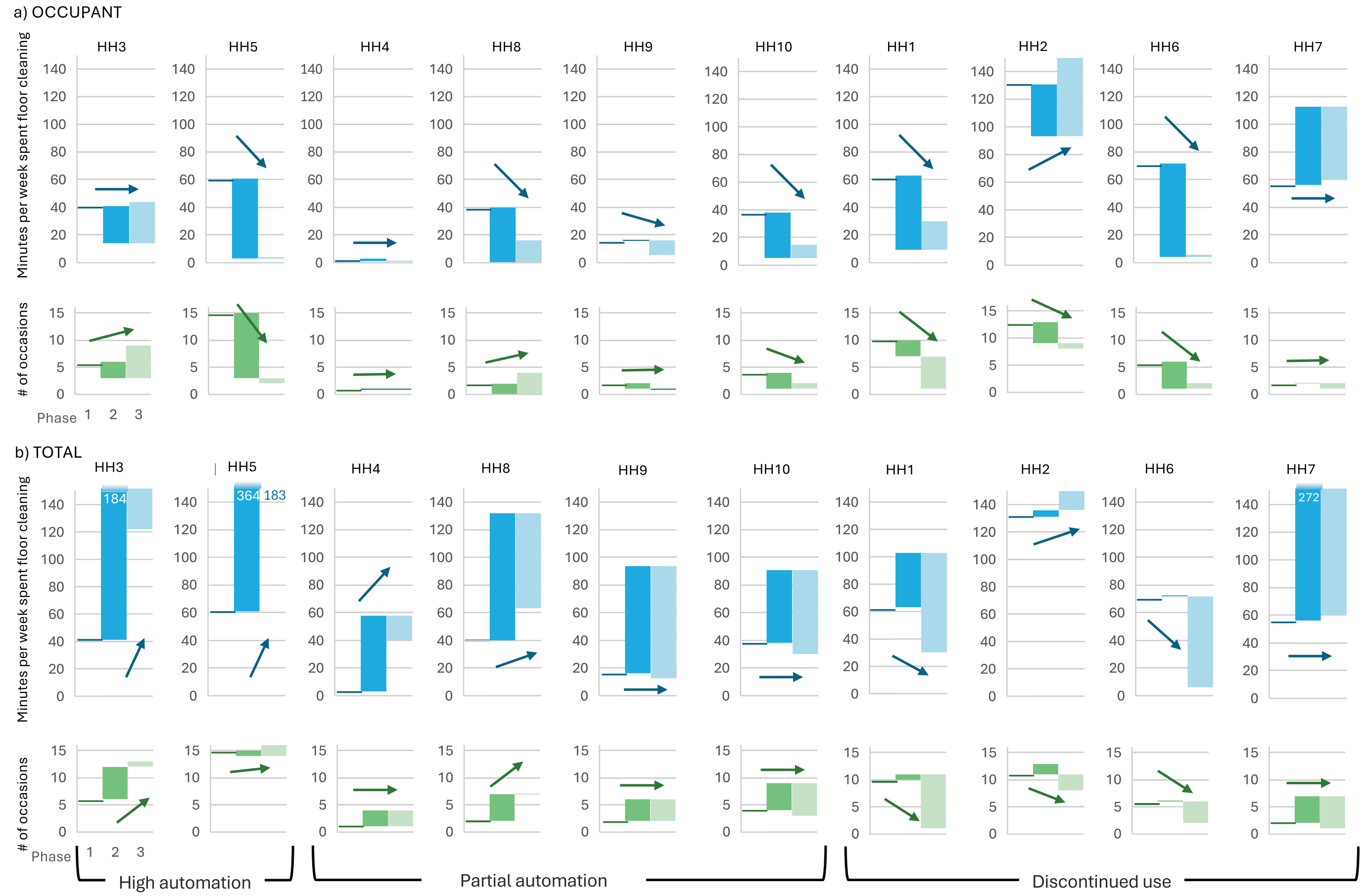

Fig. 3. Waterfall graphs indicating sequential change in time and number of occasions spent floor cleaning for 10 households across the three study phases. Arrows indicate direction of change (increase/decrease): a) floor cleaning by occupants, b) total floor cleaning which includes the automatic vacuum cleaner (AVC) in Phases 2 and 3. Phase 1 represents the pre-trial baseline, Phase 2 reflects change relative to the baseline during the 30 day trial, and Phase 3 reflects subsequent change to the trial at the long-term follow-up. HH 3,5 and 7′s results off the chart are indicated by text.

3b the overall floor cleaning, which includes the AVC usage in Phases 2 and 3. Among households with high baseline cleaning habits, overall frequency did not alter much in Phase 2, but the number of occasions for occupants carrying out the cleaning decreased, along with time spent on the activity. For instance, HH1 cleaned 10 times and spent 63 mins/week in Phase 1, shifting to 11 times per week – with seven of those instance carried out by household members themselves and for only 9 mins/week during Phase 2, consisting of quick 1–2 minute sweep ups after dinner time with a toddler. For one household (HH4) recorded floor-cleaning time increased from 3 mins/week to 58 mins/week. This pattern suggests that the AVC facilitated more frequent upkeep whilst keeping occupant involvement low (<1min/week). Fig. 3 presents the changes in time spent (duration) and number of occasions (frequency) on floor cleaning in each household, over the three phases.

Although quantitative data indicated clear time savings for the participants (illustrated in Fig. 3a where occupant time spent per week in column 2, is less than column 1), their perceptions of time were more complex. In most cases, perceived time savings broadly matched recorded reductions in manual effort (SI Table 4). However, many participants described invisible burdens associated with preparation, supervision or device maintenance (not captured in Fig. 3) which added to perceived time spent on the activity of floor cleaning. As participant 1.1 noted "*I feel like I spend the same amount of time because I have to tidy up more now before it [AVC] runs*". Such reflections discussed further in Section 4.2.4 illustrate the reconfiguration rather than removal of labour with manual effort distributed to more frequent occasions rather than fully eliminated.

4.2.3. *Long-term changes in frequency and duration of activity (aspects 3 and 6)*

During Phase 3, over one year after the trial, change from pre-trial cleaning patterns was less stark. Relative to Phase 1 baselines, long-term cleaning frequency decreased by 4 % and duration increased by 44 % (SI Fig. 2). However, occupant time spent cleaning had still dropped on average by 31 %.

Examining household level data, patterns diverge more compared to during the trial (Phase 2). Some households sustained high levels of automation (e.g. HH5: 98 % AVC usage; HH4: 75 %, SI Table 4) whilst others either reduced or entirely discontinued use. In cases of discontinued use, occupant cleaning time either reverted to pre-trial levels or declined even further than pre-trial levels (Fig. 3a). HH7, for example, recorded no net gain in time saved, nor perceived any gain by Phase 3, "*We feel the floors are being cleaned the same as before. The trial didn't change anything*" [participant 7.1]. Caution should be taken when interpreting results from Phase 3 as data collected for only the previous 7 days is likely to have missed households' 'big cleans' that appear to happen at least every month but not every week.

4.2.4. *Changes to planning and associated activities (aspects 1 and 4)*

For many households, planning and preparation time increased during the trial due to more frequent floor cleaning. Participant 7.1 reflected post-trial "*more time planning, moving and tidying but less on cleaning. Time has just shifted to different tasks*". Over time, however, several households streamlined routines to reduce preparation effort. For example, participant 3.1, reported a "*knock-on effect*" where "*we don't leave things on the floor... no more floordrobe*" and by Phase 3 the household had modified furniture layouts to accommodate the device, such as attaching bedside tables to walls to remove obstacles from the floor.

Other new activities also emerged due to automation. Most notably, households took on supervisory roles and occasional troubleshooting. Participant 4.1 described in Phase 2 "*Last week I spent two plus hours supervising [the AVC] getting stuck and being available to untangle rugs out of the rollers.*" Together, these examples illustrate how automation generated new forms of domestic labour rather than eliminating existing ones.

Additionally, the AVCs brought about companion app usage, which varied but was generally low. Seven households used the app for under an hour across the 30 day trial, typically just for activation or checking routes. Others recorded 3 to 4.5 hours of usage largely during the 'burdensome' set up phase. By Phase 3, two of the households using an AVC completely discontinued app use and reverted to pressing a manual button on the device. The rest used it for approximately one minute each time they wanted to: *"just set it off"* [participants 4.1, 9.1]; *"see where it is in a room and whether I can open the door"* [participant 9.1]; or *"check what an error is"* [participant 5.1].

4.2.5. Enabled parallelisation (aspect 8)

Responses to the question regarding parallel tasks are summarised per household in Table 4. Most participants reported using the time when the AVC was active to do domestic chores. As participant 3.1 explained "*once I cleaned all the skirting boards, another time I dusted all the spider corners… I use the [AVC] to double my cleaning effort. As the floors look cleaner it makes the stairs and other areas look more dirty, I have to keep up.*" However, some participants also reported spending the time on additional leisure and relaxation such as watching TV, reading or having a cup of tea.

Overall, across households, these patterns show that automation primarily reconfigured domestic routines and time-use patterns through intensification, fragmentation, and greater parallelisation, rather than simply reducing labour. Next, we focus on what these shifts mean for energy consumption.

Table 4
Automation enabled parallelisation reported by households.

	ID	Parallel tasks during Phase 2	Parallel tasks during Phase 3
High automation	HH3	Not relaxed, working, cleaning surfaces, bathroom and windows	Working from home, in the evening on computer (but not whilst watching TV)
	HH5	Working, making breakfast	Anything: sleeping, out of home, working, watching TV
Partial automation	HH4	Work outside home, cooking, watching TV, working at home, supervising [AVC]	Meeting, cooking
	HH8	First times supervising, then cooking, reading, out of home	Sleeping, out of home shopping
	HH9	Cooking, cleaning surfaces and vacuuming stairs, chores, laundry, supervising [AVC]	Cleaning upstairs, working, hanging out washing, watching TV
	HH10	Laundry, put out the bins, cleaning surfaces, cooking	Making lunch and dinner
Discontinued use	HH1	Child care bedtime routine, and washing up	n/a
	HH2	Other chores, laundry, cooking, surface cleaning, reading, playing with children	n/a
	HH6	Having a cup of tea, gardening, working	n/a
	HH7	Cleaning surfaces, working	n/a

4.3. Impacts of automation on energy use

4.3.1. Direct and indirect energy impacts of activity (aspect 5)

Fig. 4 presents the weekly energy use (kWh) from floor cleaning across the three study phases, distinguishing occupant operated vacuuming (blue) from AVC use (orange).

Pre-trial (Phase 1) vacuuming consumed an average of 0.38 kWh per week, compared to 0.27 kWh for automatic cleaning and 0.10 kWh for additional occupant cleaning during Phase 2. However, closer inspection of household-level trends in Fig. 4 reveal aggregate figures mask important variation depending on usage patterns and contexts.

For households 3, 5, 8, 9, 10, 1, 2 and 6, majority of energy use has shifted from conventional vacuums to AVCs in Phase 2, suggesting a strong *substitution effect*. For households 3, 5, 4, 8 and 9, total cleaning energy use even increased in Phase 2, indicating a clear *rebound effect*. As outlined in Sections 4.2.2 and 4.2.3, AVCs were operated more frequently in Phase 2, compared to pre-trial occupant cleaning. These higher frequencies across all but one household (HH5) explain the observed *rebound effects*.

Only in HH7, occupant cleaning remained dominant in terms of energy (and time) use despite automation, suggesting partial or inconsistent AVC usage. *Efficiency effects* are difficult to observe in the available data. On average, the AVCs had a lower power draw than their manual counterparts. However, a wide variation was found with the watts of the AVCs (despite being the same model across households – SI Table 5). This is presumably due to changes in settings e.g. suction power.

A year later, in Phase 3, average weekly energy use decreased to 0.13 kWh for AVCs and increased to 0.30 kWh for VCs used by occupants. However, results from HH7 skew the average result with much higher energy consumption from their VC (Fig. 4). All but one household (HH2) reported perceiving their floors were being cleaned more than or the same as before the trial. In some households (e.g., HH8 and 9), data suggest that energy use declined as the novelty effect wore off, as participant 9.1 implied "*I made much more of an effort because obviously you wanted to in the trial, one wanted to find out how good it was… but now I've sort of relaxed and I'll only stick it on when needed.*" This pattern indicates a joint *substitution* and *efficiency* effect driven by replacement of manual vacuuming and the lower wattage of AVCs. Although HH3 and 4 lowered energy consumption in Phase 3 relative to Phase 2, their energy use remained higher than in Phase 1, indicating a sustained *rebound effect*. Meanwhile, HH1, 2, and 6 discontinued AVC usage, and their energy use for VC cleaning dropped compared to Phase 1, but HH7's reversion to fully cleaning themselves with the use of VCs resulted in greater energy consumption than Phase 1.

Next, we look solely at the method of cleaning used and how much households shifted from manual sweeping and mopping to electricity consuming vacuuming. The results show a significant shift. The proportion of time using electrical methods rose sharply for the vast majority of households in Phase 2 and remained high in Phase 3 (Fig. 5a), while the proportion of cleaning occasions involving electrical appliances showed more variability (Fig. 5b). Household level data available in SI Table 6. This suggests that although AVCs were used for longer durations, manual methods continued to be intermittently employed, with qualitative insights revealing such occasions were mainly quickly sweeping a targeted zone e.g., kitchen after cooking. Overall, these insights confirm the joint occurrence of substitution and efficiency effects in many households.

4.3.2. Indirect energy impacts of other activities (aspect 6)

Another indirect energy impact not captured by smart plugs and diaries is the energy consumed by other activities conducted in the saved time. Conclusive statements about time reallocation and the energy implications are not possible, because AVC adoption can lead to broader shifts in the timing and sequencing of activities that can only be captured with full-day or −week time-use diaries. However, our results in Section

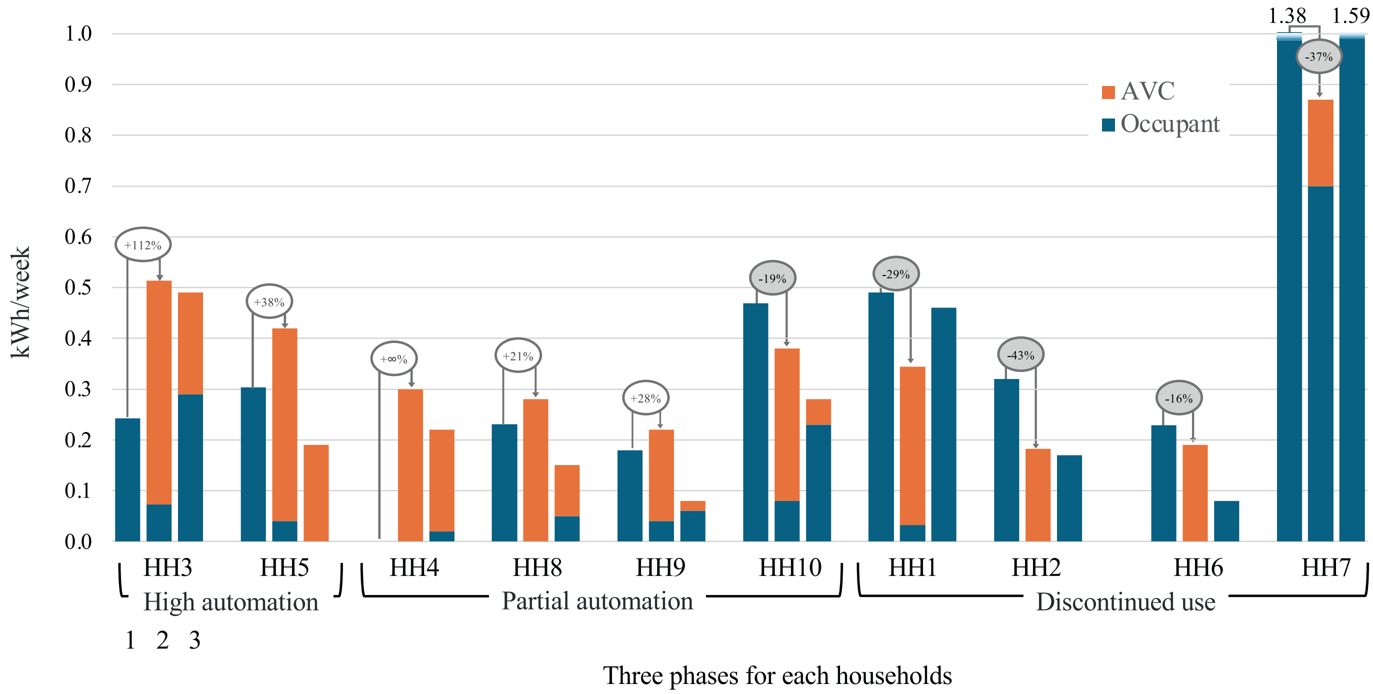

Fig. 4. Stacked clustered bar chart showing the energy use in kWh/week from floor cleaning across the three study phases for both 1) Automatic vacuum cleaner (AVC) (orange) and 2) occupant cleaning with their regular vacuum (blue).

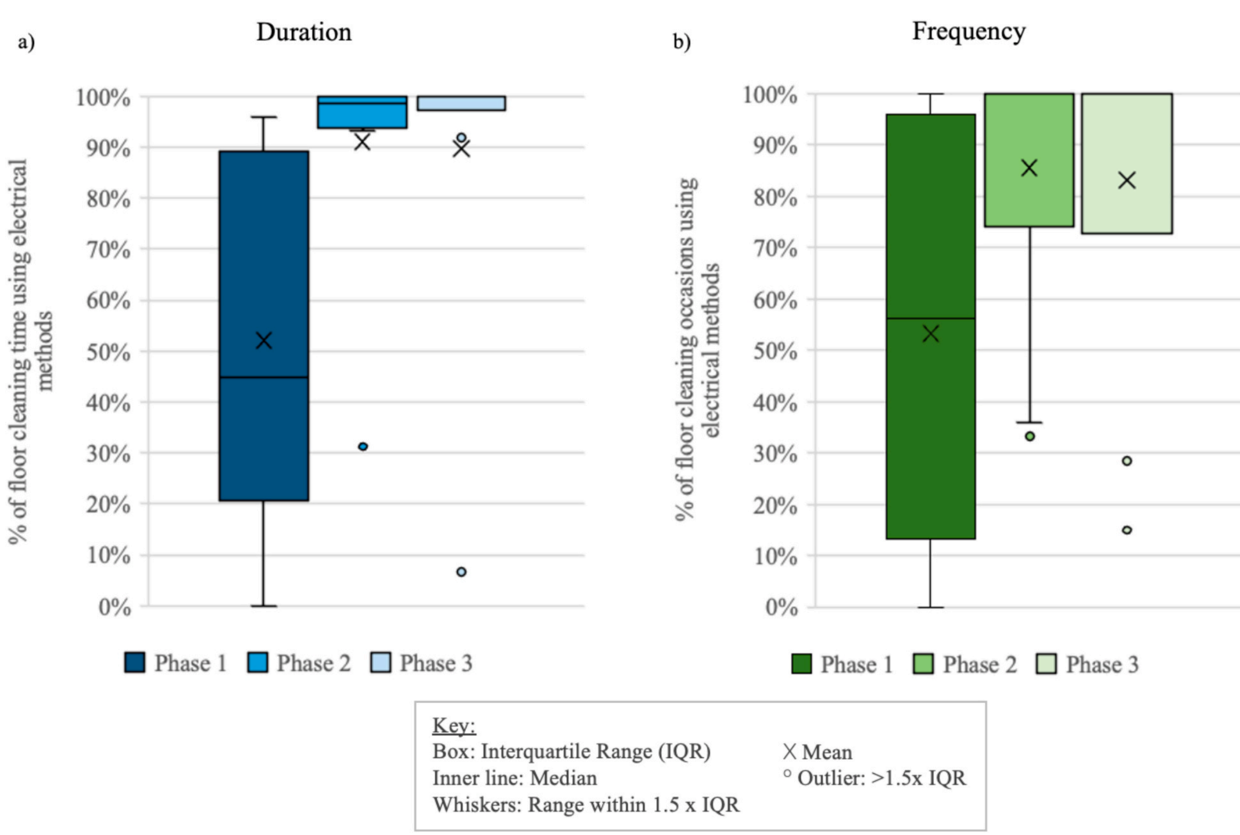

Fig. 5. Box and whisker plots illustrating the change in floor cleaning method for all households: a) the percentage of floor cleaning time using electrical methods, and b) the percentage of occasions using electrical methods.

4.2.5 provide some insights on what participants were doing while the AVCs were running. The results suggest that most participants carried out low-energy activities such as other cleaning or maintenance tasks, caregiving, reading, relaxing, or sleeping. Also, there was little evidence that parallel activities led to increased (energy-intensive) travelling, as participants were typically present or at work while the AVCs were operating. Taken together, these results demonstrate how automation produces overlapping substitution, efficiency, and rebound effects, shaped by household routines and usage patterns.

5. Discussion

Our study contributes evidence that the real-world impacts of domestic automation are shaped not only by technical performance, but by how such technologies are embedded in and interact with everyday routines. Using a time-use lens and longitudinal design, we traced direct and indirect energy effects stemming from changes in when, how, how often, and how long tasks are performed, including the parallelisation of activities. These patterns of temporal redistribution help explain why some households experienced efficiency gains or substitution effects, while others saw minimal change or additive rebound effects.

Our findings demonstrate the value of integrating Horner et al. [38]'s typology of indirect energy impacts with Bieser & Hilty [14]'s activity-aspect and time-use framing. This integrated framework allows for a more nuanced analysis of both home automation's downstream consequences and all automation with impacts on time and energy, extending beyond device-level assessments to capture dynamic behavioural interactions and cumulative impacts.

5.1. Automation and time-use patterns

To address RQ1 (how the adoption of automation alters household time-use patterns over time), our findings show that automation did not simply displace manual effort but catalysed broader behavioural adaptations, most notably increased activity frequency, added planning effort, and greater parallelisation of tasks. Rather than saving time, automation frequently redistributed domestic labour by layering new preparatory and supervisory activities onto existing routines. In particular, deliberately distinguishing between planning and execution automation yielded valuable insights. For instance, many households initially experienced increased planning efforts after adoption, reducing time savings; however, these effects diminished over time as learning and adaptation took place.

These shifts were partly contingent on household-specific factors such as pace-of-life rhythms, spatial arrangements, and material configurations, revealing how automation becomes embedded in situated practices. Taken together, such patterns contest dominant narratives of domestic automation as time-saving and instead demonstrate how it reorganises, intensifies, or reconfigures domestic labour. This mechanism-based interpretation reinforces and extends classic socio-technical insights into the co-evolution of technology and household routines, echoing recent scholarship that emphasises how automation-induced change is conditioned by domestic materiality and everyday rhythms [7,10,26,67–70].

5.2. Direct and indirect energy impacts

In relation to RQ2 (the direct and indirect energy implications of automation), our findings demonstrate that automation's energy outcomes depend less on technical efficiency and more on behavioural and temporal dynamics. Across households, planning automation (e.g., scheduling) intensified device use and contributed to additive energy demand, while execution automation enabled 'layering', increasing overall domestic activity. These behavioural pathways help explain the coexistence of substitution, efficiency, and rebound effects observed in the study.

Our differentiation into planning and execution automation also revealed that many households rarely engaged with scheduling functions. This explains that execution automation alone did not substantially reconfigure the timing of cleaning. Pre-existing habits, household rhythms, and social factors such as work schedules or family dynamics play a greater role in determining when cleaning occurred, raising questions about the extent to which automation can support load shifting or demand flexibility. These patterns illustrate how indirect impacts, including rebound effects, manifest not only in total energy used, but in when and how that energy is consumed. As AVCs draw energy primarily during charging rather than during task execution, our direct energy findings apply specifically to devices with similar charging-based profiles; however, the indirect, behaviourally mediated mechanisms we identify are not dependent on this characteristic. This multifaceted understanding aligns with Horner et al.'s taxonomy of indirect impacts, particularly behavioural, systemic, and structural dimensions and reinforces the need for integrated assessments that capture subtle but cumulatively significant shifts in household energy demand, patterns that conventional device-level efficiency metrics often miss [71].

5.3. Generalising beyond vacuums: A broader automation lens

While our study focused on AVCs, Table 1 illustrates a wider landscape of domestic automation, ranging from automated watering systems to smart locks and automated cooking devices. Many of these technologies share key characteristics: they decouple task execution from occupant presence, enable scheduling, and often operate with limited feedback on cumulative use. As shown in our framework (Table 2), such features carry significant implications for energy demand depending on how they are embedded in routines, when they operate, and what activities they displace or enable. Our findings therefore reflect underlying behavioural mechanisms rather than device-specific properties, supporting the analytical relevance of AVCs as a case through which to examine wider automation dynamics. Although these mechanisms emerged in the context of floor-cleaning automation, other forms of domestic automation may introduce additional behavioural considerations not captured in our study. In particular, user education and perceived safety may shape how confidently people rely on planning features, such as scheduling, in systems that require configuration or are viewed as risky to leave unsupervised. Together, these mechanisms suggest that small domestic devices can serve as early indicators of broader transformations in digitally mediated household energy practices. Their impacts, whether substitutional or additive, mirror patterns emerging in other domains of domestic life.

The growing presence of digitally enabled automation agents such as several listed in Table 1 (e.g., automated window cleaners, robotic lawn mowers, automated pet feeders) expands the time budgets available for substituting human tasks [72] and reshapes existing activity patterns. In some cases, these systems even introduce entirely new behaviours. The overall energy impact will depend on the cumulative use of these devices and the nature of the human activity reconfigurations they induce. If time freed through automation is not redirected towards low-energy activities, net household energy demand may rise due to the additional consumption of the devices themselves [49,60].

As automation diffuses across tasks and contexts, its aggregate impact on energy systems will depend not only on how much energy is used, but also on when that energy is demanded, and whether this timing aligns with system-level constraints or opportunities, such as dynamic time-of-use tariffs and the need for greater demand flexibility.

6. Conclusion

6.1. Implications for practice, policy and future research

Our empirical findings relate specifically to floor-cleaning automation, but they reveal behavioural mechanisms such as routine restructuring, increased task layering, and rebound effects that are likely relevant across other forms of domestic automation. Building on these demonstrated patterns, we suggest that context-responsive design and energy policy should account for how automation can increase task frequency, extend total task duration, and introduce new preparatory or supervisory demands, rather than focusing solely on device-level efficiency. These broader implications are offered as informed reflections rather than definitive generalisations.

6.1.1. Practical implications: design and consumer use

Automation technologies such as AVCs and those listed in Table 1, must be designed with greater attention to context-responsive use. Devices equipped with adaptive learning capabilities, for example for AVCs being able to recognise dirt levels, adjust to user routines, and tailor operation to actual need, could reduce redundant use and mitigate rebound effects. Importantly, such responsiveness should be coupled with transparent interfaces that make cumulative energy and time use visible to users. Providing real-time feedback on energy consumption and scheduling patterns could help users make more informed decisions about when and how frequently automation is deployed and help them manage their energy bills [73,74].

6.1.2. Policy implications: supporting sustainable automation

Existing policy frameworks such as the EU Eco-design Directive (2009/125/EC) and Energy Labelling Regulation (2017/1369) typically assess appliances based on their rated technical efficiency under standardised conditions. However, as our findings show, the real-world energy impacts of automation depend heavily on how technologies are embedded into household routines. Therefore, policy instruments must evolve to account for these indirect and behavioural dimensions. For instance, eco-labelling schemes and appliance energy ratings could be extended to include dynamic usage factors. This might involve a new category or 'behavioural risk rating' that flags devices prone to excessive or redundant use due to automation features such as remote scheduling or absence of feedback loops. These expanded labels could inform consumer purchasing decisions by highlighting not just how much energy a product uses under lab test conditions, but how its design and use-patterns may influence household-level rebound effects.

Policy tools such as public procurement guidelines and rebate schemes could also prioritise automation products that support demand-side flexibility. For example, incentives could be offered for smart devices that are responsive to grid carbon intensity signals, or that include user-facing dashboards making energy/time trade-offs transparent [75,76]. These measures would help shift market expectations away from automation as purely a convenience or luxury good, and toward its responsible integration within sustainable domestic practices. Finally, public awareness campaigns could challenge prevailing norms around convenience, hygiene, and automation, especially where these drive unnecessary or excessive use. By reframing domestic automation as a tool for sustainable time and energy management, not just labour saving, policy can help shape more climate-aligned consumption narratives.

6.1.3. Further research implications

Despite the proliferation of domestic automation technologies, research on their time use and energy implications remains narrow in scope, typically centred on short-term trials in developed countries contexts. Future studies on automation would benefit from using a similar longitudinal, mixed-methods approach to the one presented in this paper, but also including methods of 24hr time-use diaries to capture not only immediate changes in time use but also the reallocation of time. It is particularly important to examine whether automation displaces, complements, or amplifies existing labour, and how such outcomes are mediated by household characteristics, built environment, and evolving expectations of convenience and cleanliness.

6.2. Concluding remarks

As domestic automation continues to diffuse across ever greater household activities and in more and more households, its impacts on time use, household labour, and energy demand require closer scrutiny. This study uses the automation of vacuum cleaners as a demonstrative example and shows they can reduce manual effort and lower average energy consumption. However, these gains are contingent on how technologies are embedded within everyday routines. Automation does not operate in a vacuum (pun intended): it alters the timing, frequency, and social meaning of tasks. To ensure that domestic automation contributes to, rather than detracts from, goals of energy demand reduction and demand flexibility for decarbonisation, future interventions must account for behavioural dynamics, promote flexible and responsive design, and consider the diversity of domestic contexts. Addressing these challenges will be essential as households increasingly become sites of automated, digitally-mediated consumption. Only then can domestic automation become a force for low-carbon transitions rather than a source of rebound and emissions creep.

CRediT authorship contribution statement

Emilie Vrain: Writing – review & editing, Writing – original draft, Visualization, Validation, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Jan Bieser:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Charlie Wilson:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization.

Declaration of competing interest

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.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.enbuild.2025.116920.

Data availability

The datasets generated and analysed during this study are available via the UK Data Archive ReShare repository [https://reshare.ukdataservice.ac.uk/858037].

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