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Beyond the average consumer: Mapping the potential of demand-side management among patterns of appliance usage

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ABSTRACT

To support the decarbonisation of the power sector and offset the volatility of a system with high levels of renewables, there is growing interest in residential Demand-Side Management (DSM) solutions. Traditional DSM strategies require consumers to actively adjust the timing, mode, and frequency of their appliance usage to curtail or shift in time energy consumption. Therefore, overlooking the dynamic intricacies of these adjustments and assuming uniform consumption patterns across households can lead to inaccurate and untargeted recommendations in DSM programme design.

This study aims to contribute to DSM research by introducing a novel methodology for analysing energy demand and flexibility. Our primary goal is to uncover patterns in volume, timing, and mechanisms of demand management across the population. Drawing insights from engineering and social science studies, we conducted a comprehensive quantitative survey ($N = 1188$) focusing on laundry and dishwashing habits in German households. Employing statistical methods, such as hierarchical clustering, multinomial logistic regression, and analysis of variance, we identify distinct patterns, explore their determinants, and assess variations in load-shifting potential and perceived inconvenience.

Our findings reveal three key insights: 1) significant and meaningful patterns can be identified among the large diversity of dishwashing and laundry habits, 2) pattern membership is influenced by multiple and complex factors that resist a narrow categorisation and 3) households with more energy-intensive patterns tend to perceive load-shifting as more inconvenient, revealing a misalignment between flexibility potential and readiness. Importantly, our approach enables the identification of appliance usage patterns easily applicable in energy demand models. Furthermore, by integrating insights from various disciplines, this pattern-oriented methodology can inform more targeted and effective DSM interventions, thereby supporting the transition towards a highly electrified renewables-based energy system.

1. Introduction

To achieve net zero emission targets by 2050, the European Union relies on the joint decarbonisation of the electricity supply, and electrification of end-use sectors, in particular buildings and transport [1]. Indeed, the increasingly decarbonised grid, powered by renewable electricity, can provide clean end-uses, such as laundry, cooking, heating, and commuting [2,3]. However, this poses new challenges for the system operators, who have to manage rising peaks in electricity consumption [4], and to ensure a constant balance between volatile energy feed-in and withdrawal from the grid to avoid power service outages [5].

While congestion and grid balancing challenges have traditionally been tackled by reinforcing the grid and using dispatchable generation units, today these can no longer be the only solutions. Grid reinforcement is costly [6], and generation alone will increasingly struggle to fulfil the grid balancing functions against the increasing penetration of non-programmable renewable resources, and the decommissioning of fossil fuel power plants [7]. Thus, strategies to manage both sides of the supply-demand binomial are not only desirable, but necessary. Demand-Side Management (DSM) solutions comprise a set of technologies, actions, and programmes on the end user side that aim to reduce energy demand and make it flexible, adjusting its timing and/or volume in order to optimise energy systems overall [8,9].

In this context, energy demand models—notably those employing a

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bottom-up approach wherein all devices are modelled individually—can serve an important role in studying quantitatively demand flexibility, its costs, value, and contribution to the energy systems [10,11]. The typical underlying assumption posit that, as energy is derived from energy consuming household appliances, the source of flexibility will therefore derive from these appliances. Accordingly, by estimating the average energy demand per appliance, the flexibility potential of each household can be derived and aggregated up to the desired scale (e.g., local, regional, national). Nevertheless, these models are often overly optimistic [12] and provide a first-order estimate of the potential for flexibility, rather than an accurate quantification with targeted recommendations on how to mobilise. This is due to two main reasons.

First, behind each managed kW or kWh lies a greater complexity given by those factors and dynamics through which consumers change their energy service expectations, daily activities and the operation of the appliance itself [13]. For laundry specifically, this may involve, for example, choosing low-energy cycles, running a long or delayed program, shifting the entire practice in time, or washing by hand [14]. Therefore, more conceptual and empirical clarity about what exactly needs to be "managed" beyond each shifted or curtailed energy unit, kWh, is essential.

Second, while we know a great deal about the aggregated consumption at district and national level, individual household consumption is highly variable, even under the same weather conditions, technical characteristics of the system, socio-demographic and economic characteristics of households, historical consumption data, and energy prices [15]. The residual and non-negligible part of this variability has been attributed to the specific way that a technology or service is used at home (e.g. in terms of intensity and time of its use) [16]. These factors are typically represented to a limited extent in energy demand models [17]. When they are considered, they are averaged for a reduced set of socio-demographic classes [18]. As a result, inaccurate estimates of the potential for flexibility on the individual, and hence on the entire population, can misinform the design of effective policies and fail to identify target groups.

To tackle these two challenges, researchers have searched for consumption patterns in the population. Indeed, patterns allow us to zoom in on lower levels of organisation and characterisation of energy demand (e.g. from macroeconomic indicators and national aggregate consumption to individual household behaviour and energy demand at the level of single appliances), while keeping the complexity of the model manageable. For instance, studies have utilised smart meter data in order to cluster households based on daily energy demand, volume, and shape [19–22]. Households belonging to the same pattern (or cluster) show similar total consumption in terms of volume and time. However, it is not clear how, or to what extent, each pattern can engage in DSM programs, as this depends on the operation of the individual appliances and their specific mode of use. Alternatively, studies based on Time-Use Data (TUD), also referred to as time budget diary or time diary data [23], identify patterns in activity duration, time and sequence [24–26]. However, activities cannot always be unambiguously associated with the usage of a specific appliance (e.g. the activity of washing dishes does not indicate whether it is done by hand or by dishwasher). They also do not provide any information about mode of use (e.g. which temperature of washing machine was chosen when performing the laundry) [13].

To offer a more nuanced understanding of household energy consumption and facilitate the identification of effective and targeted strategies for optimising usage and managing demand, two key questions should be considered:

(i) which level of analysis (e.g., household, individual consumer, appliance usage) is most pertinent for identifying patterns relevant to DSM applications? (ii) Which variables and attributes can best characterise these patterns in order to inform the design and operation of DSM programs?

With these two fundamental questions in mind, in this paper we establish a new methodological approach to the study of energy demand and flexibility. Our primary goal is to unravel a distinct set of patterns that will enhance our comprehension of the volume, timing, and mechanisms of demand management across diverse population segments. To ensure that the proposed methodology can effectively address these multiple objectives, we employ a comprehensive approach that integrates insights from various disciplines. We rely on social practice insights in order to guide our focus on where to identify patterns, i.e. at the level of use of individual appliances rather than at the level of the household or individual consumers. Through engineering-based studies, we carefully select the attributes (i.e. frequency, mode, and time of appliance use) to characterise these patterns, ensuring their operationalizability in energy models. Additionally, we draw on practice-based and social-psychology perspectives to discern differences in pattern membership using a broad array of predictors such as socio-demographic, technological, psychological, and spatio-temporal factors. To this end, we make use of large-scale survey data that investigates in detail laundry and dishwashing habits in Germany. We focus on washing machine and dishwashers for two reasons. First, they are responsible for a relatively large share of household energy demand (~19 % of household electricity consumption [27]). Furthermore, in many studies, a majority of households have stated that they are willing to shift laundry and dishwasher use over time in exchange for economic and/or environmental benefits [28,29], therefore making these appliances a pertinent target for DSM programs. The analysis of the survey data is structured according to the following three research objectives.

First, we identify a set of distinct patterns of washing machine and dishwasher usage in German households by applying cluster analysis to washing intensity and temporality variables. This is based on the hypothesis that despite the diversity in the way people use appliances in their daily practices, a common set of shared and distributed influences (e.g. social, technological, institutional, economic) actually lead to a relatively limited number of usage variants that are commonly performed in the population [30,31]. In the following text, we will refer to these common variants as *patterns of appliance usage*.

Second, far from trying to explain the entire complexity of the phenomena that underlie the use of household appliances, and thus the energy consumption, here we test whether and how a set of socio-demographic, technological, psychological, and spatio-temporal factors are correlated with the identified patterns. This broad set of potential determinants draws on different social science perspectives.

Third, we hypothesise that, just as patterns shape energy demand, they also shape energy flexibility (i.e. the capacity and willingness to adjust the timing and/or size of the household energy demand). As such, the third objective investigates whether and how the perceived inconvenience of load-shifting—defined as a delay of the laundry or dishwashing cycle compared to the usual time—varies across the different patterns identified, and whether those who have high consumption during key periods of the day are also those who have the least hassle in shifting the appliance usage.

The rest of the paper is organised as follows: in Section 2, we position this research against the existing literature by providing an extensive review of how the appliance usage has been conceptualised and addressed depending on methodological approaches and research objectives. In Section 3, we introduce our methods. We then present the results in Section 4 and discuss their implications and limitations in Section 5. Finally, in Section 6, we conclude this paper by listing possible recommendations for policy design based on the insights of this work.

2. Conceptualisation of energy demand across different disciplines

Appliance usage data—the parameters that indicate when and how an appliance is in use—can be useful to describe the relationship between energy consumption and user behaviour. Nevertheless, they are still poorly incorporated into current energy demand models [32].

Below, in support of this argument, we first critically review how appliance usage is addressed within existing modelling studies. We then examine how two relevant social science perspectives, namely social and environmental psychology, and social practices, conceptualise energy demand and flexibility, and apply their views to justify why the analysis of appliance usage as a whole, or through individual parameters, can support better integration of social science insights into current energy modelling efforts. According to the scope of this work, we dedicate particular attention to the usage of wet appliances, i.e. washing machines, dryers, and dishwashers.

2.1. Engineering approaches to energy demand modelling

Modellers have extensively studied energy demand through various techniques, such as statistical, machine learning, meta-heuristic, stochastic/fuzzy/grey, and engineering-based approaches [32–35]. Of these, engineering-based models, which are characterised by a bottom-up, theory-driven (or rather physics-based) approach, are particularly compelling for informing programme, regulatory, and policy design in the field of Demand-Side Management. Indeed, they can offer great technical detail (e.g. dwelling properties such as geometry, envelope fabric, and appliance power rating). They can address technological changes (e.g. replacing a gas boiler with a heat pump, or shifting from a petrol-powered car to an electric one), and microsimulate appliance switch-on events at the level of the entire household or individual occupants. In the literature, three main engineering modelling approaches have been employed to model energy consumption and user behaviour.

First, empirical static models estimate the impact of household end-uses (e.g. in terms of energy consumption), considering the appliance operating power and detailed usage data. In the case of laundry [36,37], drying [37], and dishwashing end-uses [38], usage data may include frequency, mode (e.g. manual or automated) and/or a selected programme (e.g. temperature and setting) of washing and drying cycles. Hence, a set of resource-saving recommendations for consumers and policy makers, as well as guidelines for standardisation bodies, can be derived.

Examples of recommendations may involve increasing fill rates, lowering washing temperatures, reducing intensive pre-treatment habits, and avoiding hand washing [38,39]. However, apart from a few studies comparing household segment by age [40] or lifestyle [41], and using self-reported data to derive daily and weekly load profiles [42], most of these studies lack clarity regarding the intended recipients of these recommendations and their impact on the temporality of energy demand.

Second, empirical probabilistic models use self-reported or metered data on appliance usage to derive time-dependent probability distributions of appliance switch-on events [33,43]. These data can be used directly to derive a set of simulation metrics (e.g. daily frequency, time and duration of appliance use) and generate load profiles in a stochastic manner [44]. Alternatively, they can be combined with appliance-level data on average daily consumption or annual electricity consumption to weight the metrics and ensure greater model accuracy when validated at the aggregate level, i.e. district or national [45]. However, annual energy consumption statistics do not guarantee an accurate representation of the temporal and volume heterogeneity of energy consumption among households. High-resolution appliance-level data allow for more accurate analyses, but since appliance-level monitoring campaigns are costly, such data are usually scarce and based on localised samples, making them unlikely to be representative of a region or country [46].

Third, TUD-based models use time diary data: (1) to directly define the probability of switching on/off appliances similarly to empirical probabilistic models, based on the assumption that appliances are used when the corresponding activities are held [18]; (2) to simulate household occupancy profiles and, from that data, sample appliance switch-on events based on the conditional probability of performing a given activity according to time of day and number of active occupants, and considering a weighting factor given by annual energy consumption [47,48]; or (3) to explicitly model the activity sequences of household members and then associate each activity with the use of one or more appliances through a time-independent probability factor (e.g. to conform the number of switch-on events to national statistics) or simply through heuristic rules (e.g. the appliance is switched on during or at the end of the activity) [49,50]. However, the TUDs do not consider the energy intensity of appliance usage modes (e.g. programmes or washing temperature), the activity categories provide an ambiguous link to the use of a particular appliance, and their short time coverage does not allow for routine patterns to be observed [13].

In summary, while current engineering models offer valuable insights into household energy demand and flexibility, they fall short in comprehensively addressing critical aspects such as volume, timing, underlying mechanisms, and variations across the population. Hence the need to further delve into the intensity and temporal dynamics of energy consumption, while taking into account variations among households in a systematic manner. To enhance our understanding, we propose the analysis of self-reported appliance usage data. This approach can complement studies based on TUD and smart meter data. Particularly, it can help identify behavioural patterns that are relevant for DSM applications, providing a more nuanced and comprehensive perspective on the complexities of household energy dynamics. This, in turn, can improve the accuracy and relevance of current models, creating a bridge to incorporate insights from the social sciences, as explained in the following sections.

2.2. Social and environmental psychology approaches

Social and environmental psychology challenges the traditional use of simplistic heuristic rules and representation of end-user behaviour, which acts as a deterministic parameter for the sake of perfect system optimisation (typically cost minimisation) in energy demand and flexibility modelling research by engineering approaches. Based on a number of human-centred psychological theories (e.g. theory of planned behaviour, value-belief-norm theory, attitude-behaviour-context theory), they argue that social-psychological factors—beliefs, values, attitudes, emotions, personal/social norms—explain and predict the individual's behavioural intentions, and ultimately their behaviours. Here, the research interprets energy demand and flexibility as the end user's behaviour that is 'intentionally adjustable, exchangeable and optimisable' by the end user on the basis of a large number of social-psychological (e.g. attitudes, values) factors that shape and drive it. With such perspectives, researchers in this domain pay less attention to the energy consumption as a general theoretical problem, such as what energy is for and how it is consumed, but rather tend to focus on the practical task of identifying the social-psychological determinants of behaviour in specific domains (e.g. conservation and flexibility of energy demand) and promoting interventions (e.g. advice, persuasion) to trigger behavioural changes.

In the literature, numerous studies provide a broad review of relevant social-psychological factors [51–55]. Narrowing the scope to laundry and dishwashing practices, self-reported intention towards energy-saving behaviour has been shown to be correlated to attitudes in several areas, such as economic [56–58], environmental [56,58–61], comfort [56], effort [59], but also beliefs [60], social and personal norms [57,59,61], self-efficacy [56,57] and environment- and energy-related knowledge [56,58]. Whereas, for research on "demand flexibility", attitudes towards the environment [62], perceived costs [62], perceived sense of control [63,64], security and privacy concerns [64] have been shown to be correlated with household's acceptance of, and willingness to participate in, load management programmes (e.g. dynamic tariffs, direct load control) through time-shifting of washing machine and dishwasher usage. The above-mentioned studies on the social-psychological factors form the backdrop for explaining and predicting behaviour for energy conservation and flexibility. However, there are two key issues with these approaches. Firstly, they often posit that intentions lead to behaviour, i.e. if individual's intentions to perform a behaviour increase, they are more likely to actually perform it. For this reason, most studies have focused heavily on surveys to derive intentions, where people are asked to reply to "would you…?" questions rather than stating their actual behaviour (e.g. whether they use a washing machine in eco-mode). However, social-psychological factors are not necessarily actively or consciously considered during decision-making, as many of our ordinary everyday behaviours are enacted with very little conscious deliberation [65]. This primary reliance on intention tends to overlook the influence of entrenched habits—the common practice of energy modellers is to consider intentions in surveys as actual behaviour [66]—which play a significant role in behavioural change [67,68]. Therefore, we need to better understand and model how existing habits, routines, and ordinary actions shape energy consumption and mediate the change (e.g. by acting as a behavioural 'lock-in') towards greener or DSM-compliant behaviours.

Secondly, most studies aimed at understanding intervention effects within household activities often narrow their focus to individual elements, such as using lower wash temperatures [69] or handwashing frequency [70]. While these studies reveal potential triggers and levers for behavioural change, they often overlook the intricate interdependence between the various elements that constitute a habit and its energy demands. In reality, modifying one factor of a habit frequently ripples through to impact other connected factors. For instance, let's consider the relationship between laundry frequency and programme selection: higher washing frequencies enable better sorting of clothes by fabric or colour [71], potentially influencing the choice of the temperature and wash settings. Therefore, understanding how socio-psychological factors jointly influence the different elements that constitute the habit, rather than each independently, is crucial. This approach would help design more effective DSM interventions by considering complex interactions and anticipating potential rebound effects, such as reducing washing frequency at the expense of higher washing temperatures.

In this context, we advocate for collecting self-reported data on appliance usage (e.g. washing frequencies, programme types) as a means to gain deeper insights into current energy behaviours and their social-psychological drivers. By analysing how social-psychological constructs correlate to consistent patterns of appliance usage—rather than individual elements—we can determine how individuals or households translate attitudes and norms into energy behaviour. In doing so, our stance underscores the need to consider both intentions and current energy behaviour in its multiple facets for a more comprehensive understanding of energy consumption patterns and their potential change.

2.3. Social practice approaches

Researchers with a social practice perspective question energy demand as a deliberative, cognitive process, arguing that the relationship between energy and society is not defined by external factors (e.g. efficiencies of technologies presented in engineering models) and driving forces (e.g. socio-psychology-based information and persuasion campaigns), but must be understood as part of the reproduction and transformation of society itself [72]. Consequently, energy is an ingredient of practices. Together with complex and distributed influences from cultural norms and meanings, supply systems and technologies, as well as individual characteristics, mediate the way they are performed [31]. Therefore, adopting a practice-based perspective implies focusing not only on the individual elements, but on the ensembles and configurations that they take to form a practice, and how these configurations develop, change, and intersect to understand energy demand and flexibility. For example, this may involve looking at laundry practice from a broader perspective that includes the processes through which clothes and other items become 'dirty' and then get 'clean', the routinised nature of such dynamics [73], as well as examining in detail the use of washing machines and the temperature at which people do their laundry [74].

Despite a growing body of research arguing the relevance of practice approaches to understanding energy consumption, social practice-based research is often conducted through a qualitative approach. An exception is represented by TUD-based studies. While recognising that practices cannot be reduced to activity sequences and connections, analysing activity sequences through different time lenses and time scales is valuable to gain insight into how practices connect and organise over time. Examples include: analyses on an hourly basis to better understand why peak periods are formed [75] and what impact they may have in terms of carbon emissions [76]; analyses on a daily basis to understand how activities are interconnected and intersect with each other, forming the complex web of activities that constitute household's daily lives [48,77]; analyses on an annual basis to provide useful insights into the evolution of peak periods over the long term [78]. Despite the authors themselves acknowledging that activities are far from being an exhaustive proxy for practices, they argue that social practice approaches offer insights for modelling studies by providing a framework that recognises that appliance use is dynamic and variable rather than homogeneous and stable [79].

In line with this argument, we propose to collect and analyse appliance use data (e.g. frequency, mode, time of use). In this regard, we acknowledge that, just as practices cannot be reduced to activity connections, they cannot be characterised by patterns of appliance usage. However, data on appliance usage can provide insights into the energy intensity and routine nature of household habits, providing a valuable complement to the TUD analysis. Furthermore, by jointly collecting appliance usage parameters with social practice-informed constructs (e.g. waiting for the 'pile to be big enough' or the 'washing day' to do the laundry), we believe this analytical approach provides a systematic basis for examining the ways in which energy demand patterns form and change.

3. Methods

In the present work, we use a large-scale quantitative survey to draw a quantitative picture of the diversity in intensity and temporality of laundry and dishwashing habits among German households. In the following section, we first present the survey design, the measures used, the respondent recruitment process, and the final sample. Then we describe the analysis in detail from data preparation and cleaning to appliance usage pattern identification and characterisation (see Fig. 1).

3.1. Survey design

To collect data on how laundry and dishwashing habits are performed, we conducted an online survey with (N = 1188) German respondents. We organised the survey as follows: in Part A, after a short initial set of preliminary questions to screen respondents, socioeconomic and demographic attributes were requested; then Parts B.1, C, and D.1, which together constitute the core and largest parts of the survey, delved into the descriptive parameters of appliance usage for washing machine, dryer, and dishwasher, respectively (see Section 3.1.1); Part B.2 and D.2 represent an extension of B.1 and D.1 and focus on load-shifting attitudes and barriers (see Section 3.1.3); Part E consists of a set of psychometric items (see Section 3.1.2); finally, Part F closed the survey with a second set of socioeconomic and demographic variables, complementing Part A. The survey was implemented and conducted using the online platform Qualtrics [80]. For reasons of space, we present and report only the main constructs and items here, but will make the full survey available on request to those interested.[1]

[1] For those interested, we will make the collected data available upon request along with the Python script used for the analysis.

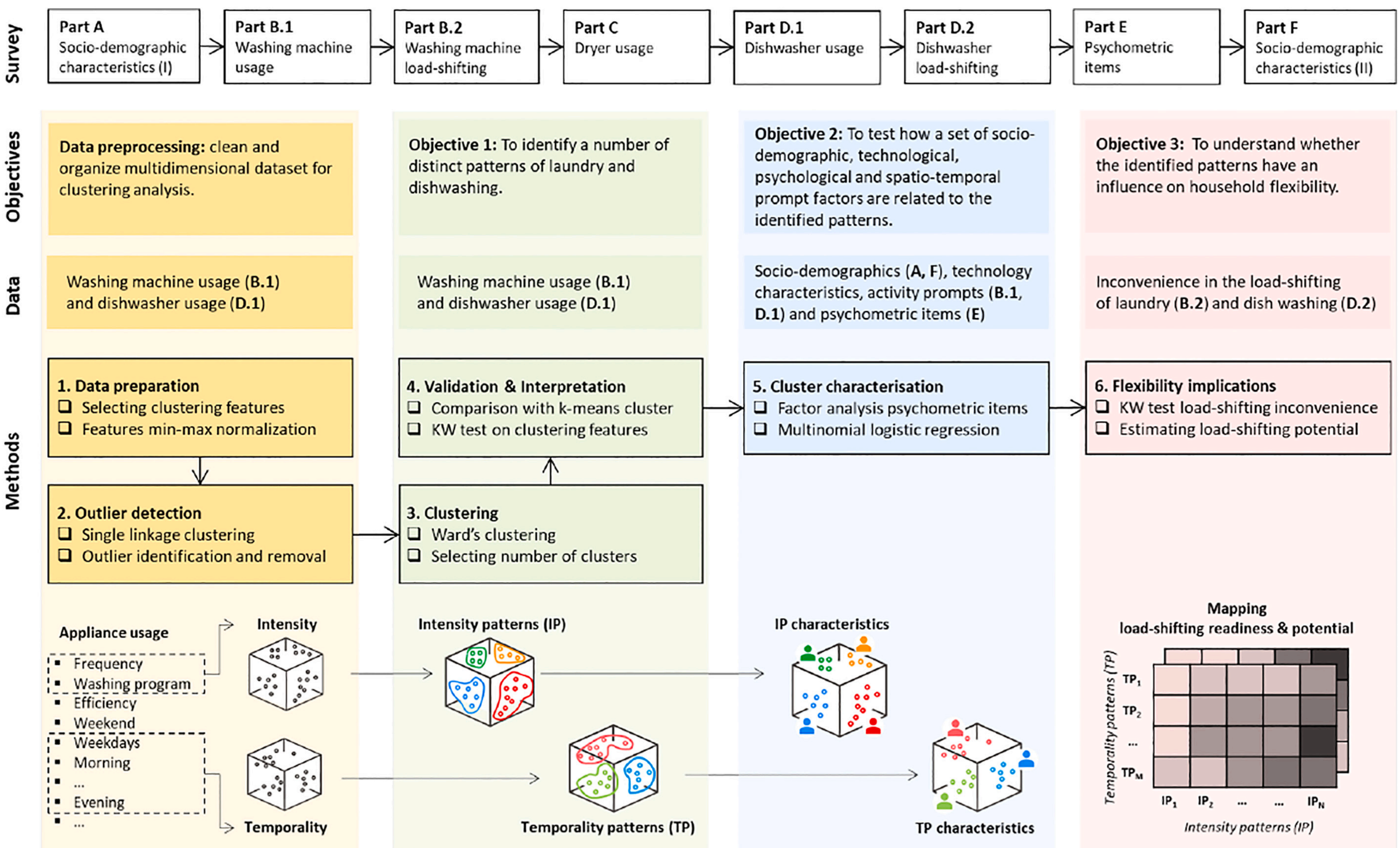

Fig. 1. Schematic representation of methods. (KW) Kruskal-Wallis test.

3.1.1. Appliance usage measures

To reveal how laundry and dishwashing habits are performed and why they are performed as they are, we selected a number of questions related to these habits and replicated them in a similar manner in Part B.1, C and D.1, appropriately adapting the elements to the specifics of each habit. To develop them, we first gathered evidence by reviewing studies from the scientific literature. Studies were identified through keyword query in the Scopus scientific literature database and by following a snowball sampling approach. Studies had to focus on laundry or dishwashing habits, show insights into different ways of performing these habits qualitatively or quantitatively, and draw direct or indirect implications on their energy demand intensity, temporality, or inter-household heterogeneity. By analysing the literature, we (i) identified and grouped the variables used to describe and analyse the different energy habits (see Table 1), (ii) studied the relevant dimensions and interdependencies between them, (iii) delved into how the habits are performed, and (iv) gathered key factors used to explain or characterise energy consumers (e.g. socio-demographic or psychological variables).

Once we had collected an extensive list of factors for each habit, we proceeded to shortlist them based on their relevance to ensure reasonable questionnaire length, the possibility of collecting reliable information through a survey, and the suitability of introducing them into an energy model. Finally, for each factor, we selected constructs already used in the literature or developed new ones. It should be noted that we also collected information on more niche behaviours and devices, such as the use of home energy management systems or the shared use of household appliances, but due to their low representation in the sample we did not take them into account when characterising laundry and dishwashing patterns.

Table 1
Categories of parameters describing wet appliance usage.

Variable	Description
Frequency	Relative frequency of appliance operation. Generally measured as the number of weekly cycles at household level or per capita [36,37,39,41].
Mode	Settings chosen for appliance operation. Depending on the purpose of the research and the respondents' expected familiarity with the appliance settings, this may refer to programmes (e.g. cotton, synthetics, easy care, mixed, wool, delicates) [37,39], additional options (e.g. no additional option, short wash, energy saving) [37,39] or temperature (e.g. cold/20 °C, 30 °C, 40 °C, 50 °C, 60 °C, 70 °C, 80 °C, above 90 °C) [36,38] of washing.
Washing system	Broad category characterising the washing system used. It can distinguish between (i) automated or hand washing [38], (ii) type of technology (e.g. vertical or horizontal axis washing machine) [36], (iii) efficiency label [41] or (iv) outsourcing through professional services (e.g. dry cleaners, laundromats, etc.) [81].
Efficiency	Filling rate of the appliance during washing cycles. Typically estimated as frequency of cycles at full load [81] or kg ratio with recommended amount [39].
Daily rhythms	Relative frequency of appliance usage throughout the day. Temporal resolution can vary from sub-hourly [78] to macro periods of the day (e.g. morning, mid-day, afternoon, evening and night) [42].
Weekly rhythms	Relative frequency of appliance use throughout the week. Usually calculated as washing frequency on weekdays and weekends [82]. Further distinction can be made between Saturday and Sunday in the case of laundry [78].
Prompts	This category includes all factors that influence the daily and weekly temporal organisation of laundry and dishwashing habits. It includes, for example, the interdependence of daily activities (e.g. loading, sorting, ironing, drying, folding, time management, eating etc.) [78,83] and socio-material arrangements (e.g. "the pile is big enough", availability of space for drying, sufficient water pressure, cheaper electricity) [37,39,74,81].
Other	This category groups factors that have been recorded less frequently in the literature: *domestic responsibility*, which refers to whether or not household members share washing responsibilities [74]; *seasonality*, as the differences in the performing of laundry and dishwashing habits across the year, usually narrowed down to a comparison between summer and winter [37]; *smart use*, which refers to the availability and frequency of use of smart features such as cycle delay or remote monitoring [37,42].

3.1.2. Appliance usage determinant factors

The survey included a wide range of questions concerning socio-demographics in Part A and F. Technical characteristics of the appliance, activity prompts, and triggers were asked in Part B.1 and D.1. These factors concerned the individual (e.g. age, gender, educational level, employment status), their household (e.g. number and composition), but also aspects related to the accommodation (e.g. type, tenure, location), available technologies (e.g. photovoltaic system, home energy management system), appliance technical characteristics (e.g. washing machine age and delayed start-up functionality), and possible activity prompts such as tendency to follow routinised patterns (e.g. "when there is the 'washing day'; I/we like routines"), environmental, material, and spatial triggers (e.g. "when the pile is big enough" or "when it is sunny") and dependencies to activity-related tasks (e.g. "when I/we have time to lay out to dry afterwards").

Although not the main scope of the research, we also asked a set of psychometric items in Part E. To this end, based on the theoretical and empirical social-psychological literature on consumer behaviour, we identified 10 social-psychological factors potentially involved in the formation of different habits: *economic attitude* and *energy-related environmental attitude* refer respectively to the consumer's consideration of financial and environmental aspects when purchasing and using domestic appliances [56,84]; *generic environmental attitudes* encompass user considerations for the urgency and desirability of policy and societal interventions to address the environmental crisis [85,86]; *energy literacy* describes an understanding of the nature and impact of household energy consumption, accompanied by the ability to apply this understanding to take effective action [84]; *self-efficacy* denotes the perceived likelihood that performing a given behaviour will produce a meaningful outcome [84]; *social norms* include both injunctive (i.e. behaviours expected to be followed) and descriptive (i.e. behaviours that others enact) influences of others on the individual's behaviour [85]; *personal norms* represents the personal feeling of obligation or moral responsibility towards a specific action in a particular situation [87]; *comfort* and *effort attitudes* are distinguished here respectively between the perceived hassle in enacting a particular behaviour and the consequences that such a behaviour has on a person's comfort and quality of life [87,88]; *justification behaviour* expresses the individual's tendency to justify less ecological behaviour through the rhetoric of compensation via more ecological behaviours in other areas [85]. For each of the aforementioned factors, we selected and adapted constructs from the literature, each consisting of two to four items, finally obtaining 23 psychometric items. To ensure consistency with the original constructs, some of the items used a 6-point agreement Likert scale, while others used a 5-point agreement scale. The exact items are reported in the Appendix (see Table 11).

3.1.3. Load-shifting readiness

In order to understand whether and how habits and routine behaviour influence consumer's readiness for DSM programmes, in parts B.2 and D.2 we presented respondents with a hypothetical load-shifting scenario for washing machines and dishwashers (See Table 2). In this case, respondents were asked to imagine that the start of the laundry or dishwashing cycle was automatically delayed by up to six hours and to indicate how inconvenient this would be for them on a 5-point Likert scale from 'insignificant' to 'severe'. To minimise possible response bias, respondents were explicitly asked to answer without considering any incentive (e.g. economic or environmental) in exchange for the delayed start.

Table 2
Load-shifting inconvenience item.

Question	Scale
Suppose that when you load your washing cycle you are asked to delay the start up for up to 6 hours in an automated way. This means you can still load the (washing machine/dish washer) whenever you want, while the cycle will automatically start later. How strong would the impact be on your need to (do the laundry/wash the dished) and/or that of your household? * *Please answer without evaluating possible economic or environmental incentives.* * *The more severe the impact, the more your daily needs are affected.*	Insignificant; minor; moderate; major; severe; don't know

3.2. Recruitment and sample description

The survey was offered in German and English, in Germany and in the German-speaking cantons of Switzerland. However, only data from German respondents was used in this study. The survey was distributed with the help of Bilendi, a market research company. The market research company sent the survey, using unique links, to people in its respondent panels who had previously agreed to participate in the research in exchange for incentives. The survey was soft-launched with 10 % of the expected panel in October 2021, and final data collection took place between November and December 2021, reaching 1188 German responses with an average response time of 18 min.

The sampling frame consisted of adults aged 18 years or older and representative of Germany in terms of age, household size, gender, and region of residence. The sample is aligned with national census statistics [89]: the age of the respondents was collected by 5-year age groups (except for groups 18–24 years old and above 75 years old), and the largest difference between the national and sample data was found for the 55–59 age group of 2 percentage points; 50.7 % of respondents were women; couples are slightly over-represented, with 40.1 % in the sample compared to 33.2 % nationally; finally, the sample has a distribution with respect to region of residence in line with the Federal Statistical Office data, and the largest difference is found in North Rhine-Westphalia, with the sample 2.8 percentage points lower than the national figure of 21.6 %.

3.3. Analysis

As depicted in Fig. 1, we structured the data analysis into six steps: (1) data preparation, (2) outlier detection, (3) clustering analysis, (4) cluster validation and interpretation, (5) cluster characterisation, and (6) flexibility implications. We used Python for the data analysis.

3.3.1. Data preparation

First, we cleaned the data by excluding cases that had not completed the entire survey. In addition, we verified that the collected cases met the criteria of quality and speed of completion. The evaluation of these two criteria was conducted solely on the basis of Part E of the survey (social-psychological items) as it was not subject to any filtering logic and thus could ensure comparability among all respondents. To meet the quality criterion, respondents had to have selected "Don't know" in less than 50 % of the items and the same answer in less than 90 % of the items. In addition, they had to have completed this section of the survey in at least 1/3 of the average response time of 1.21 min. After data cleaning, we excluded 89 cases, resulting in ($N = 1099$) valid cases.

We selected a reduced set of variables according to the following

Table 3
Variables selected for clustering analysis related to energy intensity (I) and temporality (T) of laundry and dishwashing.

Variable	Description	Laundry	Dishwas.	Unit
Frequency	Number of laundry washes per week. Directly available from survey questions	I	I	washes/ week
Avg. Temp	Average wash temperature calculated as weighted average between programme wash temperature and programme selection frequency.	I		°C
Avg Progr	Average wash energy calculated as a weighted average of the energy of the programme wash and the frequency of selection of that programme.		I	kWh
Weekday	Average washing frequency on a weekday compared to a weekend day.	T		%
Morning	Washing frequency between 06:00–09:59 compared to the rest of the day.	T	T	%
Midday	Washing frequency between 10:00–13:59 compared to the rest of the day.	T	T	%
Afternoon	Washing frequency between 14:00–17:59 compared to the rest of the day.	T	T	%
Evening	Washing frequency between 18:00–21:59 compared to the rest of the day.	T	T	%
Night	Washing frequency between 22:00–05:59 compared to the rest of the day.		T	%

criteria: first, the number of features must be appropriate to the sample size[2] and the clustering method (e.g. for Ward's clustering, it is preferable to have comparable numeric variables); second, the clustering variables must be relevant for the scope of the segmentation and they must have a correlation of less than 0.9 to avoid over-representation of the same; and third, the resulting cluster must be sufficiently diverse and meaningful to the research scope. In relation to this last point, it is important to note that the selection of variables followed an iterative process, requiring the feature set to be updated according to the clustering results and their characterisation. Moreover, as no significant segments resulted by feeding the clustering algorithm with all the available variables, we opted to conduct two distinct clustering exercises: the first using only clustering features related to the energy intensity, and the second using those related to the temporality, as reported in Table 3. All clustering features were pre-processed using Min-max normalisation to make them comparable for clustering analysis.

3.3.2. Outlier detection

Since hierarchical clustering and partitioning methods are particularly sensitive to outliers, which are rare and unevenly distributed cases in the dataset, we proceeded to identify and remove them. To do so, we followed the approach of Loureiro et al. [91], which consists of applying hierarchical Single Linkage clustering, selecting C clusters as the "cut-off level of the hierarchy", where $C = max(2, n/10)$ with n equal to the number of instances, and removing instances belonging to clusters with sizes below a certain threshold (i.e. outliers are isolated in small

[2] To our knowledge, only strongly fluctuating rules-of-thumb exist for determining recommended sample sizes: according to an overview by Sarstedt and Mooi [90], sample sizes vary roughly between 10 and 70 times the number of variables.

clusters). In this case, we remove only single-case clusters, considering that the data are inherently affected by outliers, and thus do not result from errors in data collection.

3.3.3. Clustering

We applied Ward's hierarchical clustering. Thus, initially each object represents an individual cluster, and we proceed by joining objects sequentially to form clusters of multiple objects, starting with the two closest objects. According to Ward's method, distance is defined as the change in overall within-cluster-variance, calculated applying Euclidean distances, once two groups are joined.

However, as discussed in Jain et al. [92], "Often this analysis uses a specific criterion of optimality; however, these criteria are usually arrived at subjectively. Hence, little in the way of 'gold standards' exist in clustering except in well-prescribed subdomains." [92,p. 268]. Moreover, "the feature selection process is of necessity ad hoc and might involve a trial-and-error process where various subsets of features are selected" [92,p. 271]. Therefore, our choice on the final number of clusters was mainly guided by practical considerations, such as the visual examination of the Dendrogram, and validity and stability of the clustering solution, see Section 3.3.4. In the remainder of the paper, we will use the terms "patterns" or "clusters" interchangeably to refer to common variants of appliance usage among surveyed households.

3.3.4. Validation and interpretation

The process of creating and validating the final cluster solution is iterative, largely because what defines a "good" clustering solution mainly depends on its usefulness for the research objectives. Ward's hierarchical clustering defines as many clusters as it is asked to, and so it can be difficult to identify whether the clusters thus found are in any way "real" or just artefacts of the method [93]. Here, to validate the clustering results, we tested their stability and examined whether the segmentation variables are well separated between clusters.

Stability means that the cluster membership of individuals does not change, or only changes a little when different clustering methods are used to cluster the objects. Therefore, we verified that object cluster membership with Ward's algorithm was confirmed by k-means clustering. As suggested in Sarstedt and Mooi [90], 20 % can be considered as a reference threshold for cluster affiliations change from one technique to the other, however, this percentage is likely to increase with the number of clusters used and when cluster size strongly differ.

In addition, we conducted an analysis of variance to test whether the averages of the clustering features were significantly different across clusters and post-hoc tests to perform pairwise comparisons between them. Since different tests must be applied depending on the properties of the data, first we tested normality using the Shapiro-Wilk test, and homogeneity of variance using Levene's test. Then, we selected the suitable analysis of variance and post-hoc test according to the procedure described in Sarstedt and Mooi [90]. Once the clusters were identified, we characterised them by observing the mean scores of the clustering dimensions and their distribution. In this way, we sorted and/or grouped the patterns according to common characteristics in order to better structure their comparison and analysis.

3.3.5. Cluster characterisation

To tackle the second research objective, we tested the ability of a broad set of socio-demographic, −psychological, technological, and activity prompt factors to explain the pattern membership through multinomial logistic regression models. In this case, we proceeded iteratively by selecting the most significant factors and verifying that the model converged. To make the analysis more robust, and to limit the number of independent variables, we reduced the number of social-psychological factors by means of factor analysis. Accordingly, we applied factor analysis to each construct (typically consisting of 2–4 items referring to the same social-psychological concept) and extracted the factors with eigenvalues above 1. Only one factor with an eigenvalue greater than one emerged from each construct (confirming the goodness of the constructs in addressing a single concept), which resulted in reducing the number of social-psychological variables from 23 to 10. Finally, once fitted to the regression model, we evaluated the goodness of fit using Horowitz Ben-Akiva and Lerman's Pseudo-R^2, as indicated in Hemmert et al. [94].

3.3.6. Flexibility implications

Assuming that the user has decided to enrol in a DSM programme, the response or amount of load-shifting that can actually be provided with a device is the result of two components: firstly, *baseline consumption*, in that the provision of a flexibility service at a certain point in time depends on whether the user is actually using the device at that particular instant (in fact, flexibility is usually measured as the power or energy deviation from a reference condition); secondly, the *readiness to respond*, in the sense that if the programme is not mandatory and binding, the consumer can deliberately decide to respond or override the load-shifting request. If either of these conditions is not met, the user is unable to provide flexibility services. Therefore, to answer the third research objective, we provided an estimate of both of these two components and show how this varied between the patterns.

On the one hand, we estimated the *baseline consumption*, with a first order approximation, as the average consumption per household and per population segment during key periods of the day: the morning (6:00–10:00), to understand the volume of energy that can potentially be delayed to benefit from photovoltaic power generation; and afternoon (14:00–18:00) to estimate how much energy can be shifted later at night to reduce the risk of congestion, which in the winter period occurs towards the end of this time slot and is expected to intensify further with the adoption of heat pumps and electric vehicles. In both cases, the average consumption was calculated as:

$$E_{a,t} = f_{a,t} \cdot N \cdot e_a \tag{1}$$

where $f_{a,t}$ is the relative washing frequency for appliance a and period of the day t, N is the number of cycles per day, and e_a is the mean energy consumption per cycle. In the case of laundry, we estimated the mean energy consumption using the average washing temperature. According to Stamminger et al. [42], laundry energy consumption can be considered to be, to a certain extent, linearly correlated to the value of the nominal washing temperature, $\bar{T}$. Hence, considering as a reference that a washing cycle at 60 °C and 5 kg load consumes 0.95 kWh [95], we obtained:

$$e_a = 0.95 + 0.02 \cdot (\bar{T} - 60^\circ C) \tag{2}$$

Whereas for dishwashing, we derived the mean energy consumption per cycle as a weighted sum of the selection frequency and average consumption per program. To this end, we considered the following reference energy consumption per program: ECO (50 °C) = 0.9 kWh; Normal/regular/everyday (60–65 °C) = 1.1 kWh; Intensive/pots & pans/heavy (70–75 °C) 1.44 kWh; Auto/sensor = 0.93 kWh; Gentle/delicate/glasses wash (35–45 °C) = 0.65 kWh; Quick/fast (45 °C, Jet, 30′, express) = 0.8 kWh; Quick/fast (60 °C, power, plus) = 1.3 kWh [96,97]. We reported the estimates at both the individual household and population segment levels. In this way, we highlighted which households have the highest potential for flexibility and whether or not it is relevant and appropriate to target them based on their distribution in the entire population.

On the other hand, regarding *readiness to respond*, we showed whether and how perceived inconvenience for load-shifting (Part B2 and Part D2) varied among the identified patterns. To this end, we applied the non-parametric Kruskal-Wallis test on flexibility scores (i.e. perceived inconvenience for automatic wash cycle delay up to 6 h).

4. Results

In the following, we illustrate the results of this research first for laundry and then for dishwashing habits.

4.1. Laundry

Following the research objectives, we present the results related to the analysis of laundry habits in three steps: (i) we describe the laundry patterns that emerged from the clustering analysis; (ii) we characterise the clusters identified in the previous step using socio-demographic, technology-related, social-psychological and activity prompt factors; and (iii) we present whether and how the identified clusters differ in terms of load-shifting potential.

4.1.1. Clustering laundry patterns

Through clustering analysis, we identify seven laundry intensity patterns from the cleaned sample ($N = 958$). The distinct patterns showed 100 % agreement with the classification provided by k-means clustering, and to have significant differences between clusters with respect to the two clustering dimensions. The non-parametric Kruskal-Wallis test of variance indicated that the strength of the effects is large both for *Frequency* (H(6, N = 958) = 692.7, $p < 0.001$, $\eta^2 = 0.72$) and *Average Temperature* (H(6, N = 958) = 550.2, p < 0.001, $\eta^2 = 0.57$). The results are shown as boxplots in Fig. 8. For convenience, in the following we will refer to these patterns using the acronym LI (Laundry Intensity).

Table 4 provides a comprehensive overview of the identified clusters, along with key statistics such as average washing frequency, washing temperature, and each cluster's share in the population. Supplementary boxplots in Appendix 6 offer additional insights into the distribution of cases within each cluster. Upon analysing the average washing frequency, we can classify the clusters into five distinct levels: low-frequency washing (LI1), medium-low frequency washing (LI2), medium-frequency washing (LI3 and LI4), medium-high frequency washing (LI5 and LI6), and high-frequency washing (LI7). Notably, the average washing frequency spans a range from 0.5 to 5.7 washes per week, while the washing temperature varies between a minimum of 39 °C and a maximum of 55 °C. Cluster shares exhibit slight variations, ranging from 5 % (LI7; $N = 51$) to 26 % (LI4; $N = 251$), indicating a relatively balanced distribution across the identified patterns.

The clustering analysis using the variables related to the temporality of laundry, i.e. the frequency of washing between weekdays and weekends (i.e. *Weekday*) and the frequency of washing at different times of the day (i.e. *Morning*, *Midday*, *Afternoon*, and *Evening*), resulted in the identification of 5 distinct clusters from a clean sample of ($N = 937$) cases. The clusters match for 79.5 % of the cases with the k-means clustering and are well segmented according to each clustering variable. The strength of the effects is large for all the clustering variables: *Week day* (H(5, N = 937) = 273.4, $p < 0.001$, $\eta^2 = 0.28$), *Morning* (H(5, N = 937) = 710.8, p < 0.001, $\eta^2 = 0.76$), *Midday* (H(5, N = 937) = 367.1, p < 0.001, $\eta^2 = 0.53$), *Afternoon* (H(5, N = 937) = 502.6, p < 0.001, $\eta^2 = 0.76$), and *Evening* (H(5, N = 937) = 445.1, p < 0.001, $\eta^2 = 0.0.47$). We will refer to these patterns with the acronym LT (Laundry Temporality).

In Table 5, we provide a concise overview of each temporality pattern, accompanied by key statistics. Our analysis reveals a notable distinction between routinised patterns (LT1, LT2, and LT3) and non-routinised patterns (LT4, LT5, LT6). The routinised patterns exhibit a smaller size and display a strong inclination for laundry during specific periods of the day, with a tendency to wash less frequently on weekends. Conversely, the non-routinised patterns show a less distinct preference for specific times of the day and days of the week. When comparing these patterns with intensity patterns, we observe a slightly larger range of variation in the population share across clusters, ranging from 6 % (LT2; $N = 58$) to 38 % (LT6; $N = 365$).

Table 4
Laundry intensity patterns.

ID	Description	Frequency [Washes/ week]	Temperature [°C]	Share [%]
LI1	**Low Frequency, Slightly Lower Temperature.** It is characterised by infrequent washing, approximately once every fortnight, and displays a slightly lower average washing temperature compared to the overall sample.	0.5	43	10
LI2	**Low to Medium Frequency, Higher Temperature.** This group exhibits a medium washing frequency, and generally favours higher washing temperatures compared to the overall sample.	1.1	55	14
LI3	**Medium Frequency, Lowest Temperature.** Households of this group feature a medium washing, and exhibit the lowest average washing temperature among all clusters.	1.5	39	22
LI4	**Medium Frequency, Average Temperature.** This group holds the largest cluster size ($N = 251$), and demonstrates a washing frequency similar to LI3 and an average washing temperature similar to the sample average.	1.5	47	26
LI5	**Medium to High Frequency, Lower Temperature.** Members of this cluster display a medium to high washing frequency, and opt for a washing temperature lower than the sample average.	3.5	40	6
LI6	**Medium to High Frequency, Higher Temperature.** Household in this cluster perform laundry with the same washing frequency of LI5, but chooses washing programs with temperatures approximately 10 °C higher than those selected by LI5.	3.5	50	14
LI7	**High Frequency, Average Temperature.** This cluster engages in laundry with the highest frequency, conducting 5 or more cycles per week, and keep an average washing temperature comparable to the overall sample average.	5.7	47	5
	Whole sample	2.0	46	100

4.1.2. Characterising laundry patterns

The multinomial logistic regression models showed good model fit for both laundry intensity pattern membership (Model 1: $\chi^2(276, N = 832) = 558.7$, p < 0.001, $R^2_{MFH} = 0.168$) and laundry temporality pattern membership (Model 2: 2: $\chi^2(230, N = 819) = 465.9$, $p < 0.001$, $R^2_{MFH} = 0.165$).[3]

In Table 6, we report the results for the model of laundry intensity (Model 1) considering as reference pattern LI4. The results show that LT1 is associated with smaller households than LI4, and notably both the linear and quadratic terms are significant. Compared to LI4, clusters with a similar washing frequency (i.e. LI2 and LI3) are more likely to be respondents aged 65 and over. Between the two clusters, LI2, which has

[3] According to Hemmert et al. [94], McFadden-Horowitz pseudo R^2 is the recommended measure for model fit. For a sample size >200 cases and a distribution of the observation between the categories of the dependent variable >1.6, 0.09 < R^2_{MFH} < .17 indicates a good model fit, while R^2_{MFH} > .17 is an excellent model fit.

Table 5
Laundry temporality patterns. Abbreviations: (WD) Weekday; (MO) Morning; (MI) Midday; (AF) Afternoon; (EV) Evening.

ID	Description	WD [%]	MO [%]	MI [%]	AF [%]	EV [%]	Share [%]
LT1	**Routinised Morning Washers.** This group prefers washing in the morning, with a slightly stronger inclination towards week-days.	69	77	16	4	1	9
LT2	**Routinised Midday Washers.** Members of this cluster have a strong preference for washing during midday, and they also slightly favour weekdays.	65	5	77	16	1	6
LT3	**Routinised Afternoon Washers.** This group shows a strong preference for washing in the afternoon, with a slight tilt towards weekdays.	78	9	26	52	12	7
LT4	**Flexible Afternoon/ Evening Washers.** This cluster generally prefers washing in the afternoon and evening, with a particularly higher preference for evening washing	40	1	12	39	42	11
LT5	**Midday to Afternoon Washers.** Members of this cluster exhibit a general preference for washing during midday and afternoon.	42	5	34	39	19	26
LT6	**Time-Homogeneous Washers.** This is the largest group, and their washing frequency remains almost the same throughout the day.	42	31	28	24	14	38
	Whole sample	48	22	30	29	17	100

a higher washing temperature, is also characterised by a higher proportion of men, people who work from home, and people who have a shared or private dryer, than LI4. In contrast, cluster LI3 has a lower washing temperature, but no other factors appear to be significantly different from LI4. On the other hand, the higher frequency clusters are characterised by larger households, though the quadratic term has a non-significant effect. Among them, LI5, which washes at a lower temperature stands out as having a lower *Justification behaviour* score. Furthermore, LI7 is associated with more women, home-workers, wealthier households, and respondents, indicating that they wash whenever they have the opportunity or for no specific reason. In general, it is surprising to observe that neither environmental nor economic attitudes proved to be a significant distinguishing factor between LI4 and the other patterns.

As for the model related to laundry temporality patterns (Model 2), we report the results in Table 7. We chose LI5 as the reference, which consists of households that do not have a clear preference for washing at specific times of the day, but in general tend to avoid the morning (06:00–10:00). The results show that LI1, which has a marked preference for washing in the morning, is associated with smaller, older, and retired households. These households are also less likely to have a tumble dryer and a photovoltaic system and tend to wash when they have time to fill the laundry, as well as considering preferred days and weather conditions. Cluster LI2, which prefer to wash in the midday time slot (10:00–14:00), is characterised by retirees or part-time workers, is less likely to have a PV system and a dryer, and, as expected, less frequently states that they wash “whenever possible”. Like LT1, LT3 is also characterised by older people, but being retired is not a significantly different factor. On the other hand, comparing LT5 with the non-routinised clusters, we can observe that LT4, which has a less rigid preference for afternoon and evening washing, is characterised by smaller households composed of full-time workers, and more unlikely to follow the weather condition in deciding when to wash. Furthermore, LT6, which is composed of respondents who reported having no preference for washing time, are typically young, and dependent mainly on weekly rather than daily work rhythms.

4.1.3. Load-shifting potential across laundry patterns

As discussed in Section 3.3.6, the flexibility potential depends on two components: energy consumption, i.e. the actual volume of kWh or kW that can be shifted or curtailed, and the consumer’s readiness to shift or reduce it on the basis of DSM requests. We reported an estimate of these components in the form of heatmaps in Figs. 2 and 3. In each of the heatmaps, every cell $x_{i,j}$ represents an individual household or population segment classified as belonging to the laundry intensity cluster LI_i and the laundry temporality cluster LT_j. The colour gradation indicates the value of the indicator associated with each graph (e.g. the average energy consumption during a time slot or the perceived inconvenience of load-shifting).

With regard to estimated energy consumption, we report results per household (see Fig. 2.a and c) to show how different temporality and intensity patterns influence estimated energy consumption and per population segments (see Fig. 2.b and d). Results per population are calculated by weighting the individual household energy consumption against the pattern distribution in the sample,[4] which is representative of Germany, to provide insights into the overall relevance of different patterns. From Fig. 2.a, we can observe that those who consume more energy in the morning hours are the segments with higher washing frequency and temperature (LI6 and LI7), when combined with temporality patterns that prefer washing in the morning hours in a routinised (LT1) or non-routinised (LI6) manner. Similarly, the households who consume the most energy in the afternoon are those with a higher frequency and temperature of washing (LI6 and LI7) and non-routinised patterns with a slight preference for the later hours of the day (LI4 and LI5). However, if we compare these results with the share of these segments in the total population, we can understand how each segment actually contributes to the estimated total energy consumption in these periods of days. Comparing Fig. 2.b with a, it emerges that, in absolute terms, most of the consumption in the morning hours is due to non-routinised (LT6) and medium-high washing frequency (LI4, LI5, LI6 and LI7) households.

Fig. 3 shows, in the form of a heat map, the perceived inconvenience for load-shifting of different segments of the population. Compared to the previous graphs, each cell also reports the share of the segment (in percentage points) in the sample. The top row labelled “All” reports the same parameters by segmenting the sample only on the basis of the clusters related to laundry intensity. Similarly, the column “All” on the right does the same for the clusters related to laundry temporality. In general, two trends can be observed. First, moving from the left side to the right side, and thus from lower to higher wash intensity clusters, the inconvenience given by the delay of the wash cycle, even if automated, becomes more severe. Second, along the vertical axis, although less clearly, the bottom clusters (i.e. LT4, LT5, LT6), which are those

[4] The estimate is obtained by multiplying the individual-level indicator by the number of households belonging to the same intensity and temporality pattern in a sample of 1000 households.

Table 6
Multinomial logistic regression coefficients and standard deviations of predictors of laundry intensity patterns membership. Results statistically significant at: † 10 % level; * 5 % level; ** 1 % level; *** 0.1 % level.

Ref. = LI4	Model 1: Laundry intensity					
	LI1	LI2	LI3	LI5	LI6	LI7
Constant	3.03 (1.93)	0.87 (1.55)	−1.72 (1.35)	−4.65* (2.14)	−5.48***(1.64)	−7.56** (2.59)
Household size	−3.78*** (0.75)	−0.64 (0.60)	0.41 (0.45)	1.53 * (0.62)	1.69** (0.53)	1.68* (0.77)
Household size^2	0.51*** (0.13)	0.04 (0.12)	−0.06 (0.09)	−0.13 (0.10)	−0.18* (0.09)	−0.14 (0.12)
Age (<30 y/o)						
30–64 y/o	−0.37 (0.58)	0.18 (0.45)	0.73† (0.38)	−0.02 (0.55)	0.53 (0.43)	0.84 (0.74)
≥65 y/o	0.64 (0.76)	1.95** (0.65)	1.39* (0.56)	0.57 (0.84)	0.84 (0.68)	1.76 (1.11)
Gender (female)						
Male	0.33 (0.32)	0.47† (0.27)	−0.06 (0.23)	−0.58 (0.36)	−0.38 (0.28)	−1.07* (0.45)
Tenure (tenant)						
(Co-)owner	−0.27 (0.44)	−0.28 (0.35)	−0.17 (0.29)	−0.11 (0.45)	0.14 (0.35)	0.07 (0.52)
Accommodation (Flat)						
(Semi)detached	−0.54 (0.48)	0.34 (0.39)	0.25 (0.32)	0.32 (0.51)	−0.27 (0.39)	0.67 (0.57)
Terraced	1.26† (0.72)	1.05† (0.61)	0.64 (0.56)	0.98 (0.70)	0.65 (0.60)	0.79 (0.84)
Location (<20k inhab.)						
20k–100k inhab.	−0.88* (0.42)	−0.40 (0.35)	−0.05 (0.29)	0.13 (0.46)	−0.08 (0.35)	0.20 (0.55)
>100k inhab.	−0.38 (0.38)	0.17 (0.33)	−0.03 (0.29)	0.51 (0.43)	−0.06 (0.34)	−0.12 (0.55)
University degree (no)						
Yes	−0.17 (0.36)	−0.04 (0.29)	0.17 (0.24)	−0.32 (0.38)	−0.04 (0.29)	−0.31 (0.45)
Working status (full-time)						
Part-time	0.50 (0.58)	0.12 (0.46)	−0.30 (0.36)	−0.46 (0.53)	0.18 (0.41)	0.60 (0.57)
Not working	1.44† (0.77)	−0.08 (0.73)	−0.05 (0.57)	−0.53 (0.91)	−0.28 (0.73)	1.21 (1.05)
Retired	0.69 (0.57)	−0.89† (0.50)	−0.70† (0.42)	−0.85 (0.66)	−0.49 (0.53)	−0.17 (0.86)
Other	−0.20 (0.87)	−0.85 (0.68)	−0.29 (0.52)	−0.26 (0.74)	−0.43 (0.67)	−0.85 (1.40)
Home-office (no)						
Yes	0.08 (0.52)	−0.91* (0.46)	0.19 (0.32)	0.26 (0.48)	−0.06 (0.38)	1.04* (0.53)
Income (<1300€)						
1300–1699€	−0.19 (0.51)	−0.52 (0.48)	−0.45 (0.42)	0.21 (0.62)	0.01 (0.58)	−0.27 (1.59)
1700–2599€	−0.41 (0.50)	−0.48 (0.43)	−0.54 (0.38)	−0.66 (0.60)	−0.20 (0.51)	1.16 (1.22)
2600–3599€	0.56 (0.59)	−0.75 (0.53)	−0.02 (0.43)	0.06 (0.63)	0.15 (0.55)	1.87 (1.21)
>3600€	0.44 (0.71)	−0.22 (0.54)	−0.71 (0.47)	−0.59 (0.69)	0.32 (0.57)	2.26† (1.23)
n.a.	0.70 (0.77)	−0.14 (0.64)	−0.25 (0.55)	−1.33 (0.97)	−0.53 (0.73)	1.55 (1.32)
Photovoltaic system (no)						
Yes	0.08 (0.66)	0.84† (0.43)	0.26 (0.39)	−0.71 (0.73)	0.59 (0.43)	0.84 (0.60)
Dryer (no)						
Private	−0.28 (0.36)	0.54† (0.29)	0.57* (0.24)	−0.09 (0.37)	0.08 (0.29)	0.42 (0.48)
Shared	0.84 (0.60)	1.34** (0.51)	0.47 (0.47)	−0.80 (0.92)	−0.46 (0.64)	−0.78 (1.26)
Use of start-delay (no)						
Yes	−0.33 (0.51)	0.56† (0.33)	0.04 (0.28)	0.22 (0.41)	0.55† (0.30)	−0.78 (0.55)
Age washing machine (<3 y)						
3–6 y	−0.51 (0.41)	0.07 (0.33)	0.42 (0.27)	0.01 (0.39)	0.14 (0.31)	0.11 (0.48)
6–9 y	−0.14 (0.57)	0.89* (0.44)	0.65† (0.39)	0.38 (0.58)	0.22 (0.48)	−0.25 (0.83)
>9 y	0.39 (0.44)	0.19 (0.40)	0.04 (0.34)	−0.32 (0.52)	−0.68 (0.45)	−0.73 (0.66)
Prompts (no)						
Daytime constr.	−0.18 (0.42)	−0.45 (0.38)	−0.03 (0.30)	−0.10 (0.47)	−0.13 (0.37)	−0.66 (0.73)
Free time before	−0.26 (0.35)	0.62* (0.29)	0.47† (0.24)	−0.01 (0.39)	0.42 (0.30)	1.36** (0.50)
Fixed day	−0.19 (0.45)	0.36 (0.35)	0.61* (0.29)	0.52 (0.45)	0.42 (0.36)	0.32 (0.57)
Recursive	0.69 (0.44)	−0.06 (0.32)	0.24 (0.28)	−0.29 (0.41)	0.14 (0.33)	−0.04 (0.49)
Occasional	−0.08 (0.51)	0.28 (0.42)	0.30 (0.35)	−0.08 (0.57)	0.11 (0.44)	−0.40 (0.75)
Weather	0.24 (0.43)	−0.48 (0.42)	0.26 (0.32)	0.47 (0.45)	0.35 (0.37)	0.21 (0.56)
No reason	0.54 (0.77)	0.08 (0.68)	0.68 (0.61)	0.79 (0.79)	0.48 (0.74)	2.60** (0.91)
Social-psychological						
EconAtt	−0.15 (0.19)	−0.07 (0.16)	−0.18 (0.13)	−0.09 (0.21)	−0.02 (0.16)	0.01 (0.23)
EnvAttEnergy	0.02 (0.17)	0.20 (0.15)	0.17 (0.12)	0.16 (0.20)	0.02 (0.15)	0.18 (0.24)
EnvAttGeneric	0.13 (0.16)	−0.03 (0.14)	−0.15 (0.12)	0.08 (0.19)	0.14 (0.14)	0.09 (0.23)
Effort	−0.08 (0.22)	0.16 (0.19)	0.07 (0.16)	−0.55* (0.24)	−0.32† (0.19)	−0.18 (0.29)
ComfAtt	0.06 (0.33)	−0.23 (0.30)	0.10 (0.26)	0.69† (0.38)	−0.11 (0.31)	−0.22 (0.51)
PerNorms	−0.14 (0.25)	0.02 (0.20)	0.01 (0.17)	−0.03 (0.26)	−0.01 (0.20)	−0.06 (0.31)
SocNorms	−0.04 (0.17)	−0.20 (0.15)	−0.13 (0.12)	−0.32† (0.19)	−0.08 (0.15)	−0.05 (0.23)
EneLit	0.18 (0.23)	−0.17 (0.20)	−0.09 (0.17)	0.25 (0.27)	0.22 (0.22)	−0.21 (0.33)
SelfEff	−0.15 (0.21)	−0.05 (0.19)	0.12 (0.16)	0.21 (0.26)	0.06 (0.19)	0.05 (0.31)
Justification	−0.06 (0.17)	−0.01 (0.14)	−0.17 (0.11)	0.52** (0.20)	−0.04 (0.14)	−0.16 (0.19)
	N = 832					
	$R^2_{MFH} = 0.168$					

associated with less-routinised behaviour, report a higher degree of inconvenience associated with laundry load-shifting. These results are confirmed by the Kruskal-Wallis test, which indicates that the perceived inconvenience of load-shifting is significantly different, with small effects, between both patterns of laundry intensity ($H(7, N = 959) = 28.96, p < 0.001, \eta^2 = 0.035$) and temporality ($H(6, N = 937) = 11.61, p = 0.041, \eta^2 = 0.010$).

4.2. Dishwashing

Following the same organisation as the analysis of laundry habits, here we present results related to the analysis of dishwashing habits,

Table 7
Multinomial logistic regression coefficients and standard deviations of predictors of laundry temporality patterns membership. Results statistically significant at: † 10 % level; * 5 % level; ** 1 % level; *** 0.1 % level.

Ref. = LT5	Model 2: Laundry temporality				
	LT1	LT2	LT3	LT4	LT6
Constant	−3.50 (2.30)	0.75 (2.33)	−5.80* (2.36)	1.87 (1.56)	1.02 (1.08)
Household size	−1.19* (0.59)	−0.75 (0.65)	0.00 (0.82)	−1.09* (0.51)	−0.40 (0.38)
Household size^2	0.22* (0.10)	0.19† (0.11)	−0.02 (0.17)	0.16† (0.09)	0.09 (0.07)
Age (<30 y/o)					
30–64 y/o	2.53† (1.34)	0.53 (1.27)	3.14* (1.30)	−0.77† (0.43)	−0.73* (0.32)
≥65 y/o	3.68** (1.42)	0.76 (1.37)	3.76** (1.37)	−0.41 (0.79)	−0.85† (0.50)
Gender (female)					
Male	0.37 (0.35)	−0.17 (0.39)	0.40 (0.34)	−0.06 (0.28)	0.05 (0.20)
Tenure (tenant)					
(Co-)owner	0.39 (0.44)	0.09 (0.51)	0.62 (0.45)	0.59 (0.38)	0.40 (0.26)
Accommodation (flat)					
(Semi)detached	0.55 (0.48)	−0.46 (0.58)	−0.02 (0.50)	0.53 (0.42)	0.53† (0.28)
Terraced	0.49 (0.62)	0.30 (0.73)	0.29 (0.68)	−1.32 (1.09)	0.58 (0.41)
Location (<20k inhab.)					
20k–100k inhab.	0.71 (0.44)	0.52 (0.48)	0.70 (0.47)	0.47 (0.40)	0.48† (0.26)
>100k inhab.	−0.52 (0.43)	−0.75 (0.46)	0.51 (0.42)	0.43 (0.35)	−0.31 (0.24)
University degree (no)					
Yes	0.24 (0.38)	−0.07 (0.45)	0.00 (0.36)	0.07 (0.30)	0.33 (0.21)
Working status (full-time)					
Part-time	0.21 (0.69)	1.78** (0.63)	0.25 (0.55)	−0.13 (0.41)	0.06 (0.30)
Not working	1.03 (0.86)	0.55 (1.05)	−1.04 (1.15)	−0.47 (0.62)	−0.14 (0.49)
Retired	1.19† (0.66)	2.12** (0.71)	0.76 (0.62)	−1.36* (0.68)	0.37 (0.39)
Other	2.63* (1.07)	0.49 (1.43)	2.31* (0.98)	−1.39† (0.71)	−0.48 (0.48)
Home-office (no)					
Yes	0.35 (0.61)	0.59 (0.64)	0.64 (0.49)	−0.36 (0.38)	0.12 (0.27)
Income (<1300€)					
1300–1699€	−0.75 (0.65)	−0.64 (0.69)	−0.03 (0.61)	−0.63 (0.51)	0.40 (0.38)
1700–2599€	0.05 (0.53)	0.34 (0.55)	−0.41 (0.55)	−0.64 (0.46)	−0.02 (0.35)
2600–3599€	−0.14 (0.61)	−0.24 (0.67)	−0.38 (0.61)	−0.94† (0.52)	−0.38 (0.38)
>3600€	−0.75 (0.69)	−1.18 (0.82)	−1.02 (0.69)	−0.67 (0.54)	−0.17 (0.40)
n.a.	0.64 (0.76)	−1.23 (1.24)	1.27† (0.73)	−0.11 (0.69)	0.47 (0.54)
Photovoltaic system (no)					
Yes	−1.37† (0.75)	−1.90† (1.15)	−0.57 (0.58)	−1.23* (0.54)	−0.24 (0.29)
Dryer (no)					
Private	−0.68† (0.36)	−0.73† (0.41)	−0.52 (0.36)	−0.60† (0.32)	−0.34 (0.22)
Shared	−1.84 (1.17)	−1.69† (1.01)	−1.15 (0.86)	−0.48 (0.53)	−0.24 (0.38)
Use of start-delay (no)					
Yes	−0.22 (0.54)	−0.09 (0.59)	0.61 (0.42)	0.13 (0.34)	0.45† (0.23)
Age washing machine (<3 y)					
3–6 y	−0.26 (0.43)	0.12 (0.50)	0.66 (0.43)	0.07 (0.34)	−0.12 (0.23)
6–9 y	−0.61 (0.58)	−0.39 (0.67)	−0.46 (0.66)	0.43 (0.46)	−0.17 (0.34)
>9 y	0.28 (0.49)	0.56 (0.56)	0.74 (0.51)	0.28 (0.43)	0.01 (0.30)
Prompts (no)					
Daytime constr.	−1.05† (0.62)	−0.86 (0.60)	0.02 (0.48)	−0.29 (0.40)	0.56* (0.26)
Free time before	−1.02** (0.39)	−0.87* (0.42)	−0.58 (0.37)	−0.17 (0.31)	−0.03 (0.22)
Fixed day	1.19* (0.47)	0.07 (0.57)	1.08* (0.43)	0.06 (0.37)	0.58* (0.26)
Recursive	−0.65 (0.41)	−0.29 (0.50)	−0.40 (0.40)	−0.18 (0.35)	−0.00 (0.24)
Occasional	−1.15† (0.60)	−0.23 (0.58)	−0.21 (0.49)	0.03 (0.40)	−0.29 (0.30)
Weather	0.96 *(0.41)	−0.36 (0.52)	−0.02 (0.48)	−0.90† (0.53)	0.23 (0.28)
No reason	−0.23 (0.76)	−0.45 (0.90)	−0.05 (0.80)	−0.41 (0.75)	0.44 (0.51)
Social-psychological					
EconAtt	0.32 (0.21)	−0.04 (0.22)	−0.10 (0.18)	−0.09 (0.15)	−0.03 (0.11)
EnvAttEnergy	0.26 (0.19)	−0.31 (0.21)	0.42* (0.19)	−0.15 (0.16)	−0.15 (0.11)
EnvAttGeneric	0.26 (0.18)	0.26 (0.20)	−0.08 (0.18)	0.08 (0.16)	0.08 (0.11)
Effort	−0.32 (0.24)	0.72* (0.28)	0.49* (0.24)	−0.01 (0.19)	0.12 (0.13)
ComfAtt	−1.01** (0.39)	0.69† (0.41)	−0.37 (0.38)	−0.26 (0.33)	0.10 (0.23)
PerNorms	−0.09 (0.25)	0.22 (0.27)	−0.07 (0.26)	0.04 (0.21)	−0.06 (0.15)
SocNorms	0.05 (0.20)	0.32 (0.21)	0.07 (0.19)	0.20 (0.15)	0.14 (0.11)
Innovation	0.09 (0.25)	−0.21 (0.28)	0.29 (0.26)	0.08 (0.22)	−0.09 (0.15)
EneLit	−0.10 (0.25)	0.51† (0.27)	0.35 (0.25)	0.10 (0.20)	0.14 (0.14)
SelfEff	−0.08 (0.18)	−0.06 (0.20)	−0.32† (0.17)	−0.12 (0.15)	0.01 (0.10)
	N = 819				
	$R^2_{MFH} = 0.165$				

showing the patterns that emerged from the clustering analysis, the results of multinomial logistic regressions, and the estimates of load-shifting potential.

4.2.1. *Clustering dishwashing patterns*

Applying clustering analysis to the dishwashing intensity variables (i.e. frequency and average energy of the washing cycle) on a clean sample ($N = 684$), we identified six clusters. The results were stable at 93 % with respect to k-means clustering and clusters strongly differed in terms of frequency ($H(5,N = 684) = 622.8$, $p < 0.001$, $\eta^2 = 0.91$) and estimated average energy consumption ($H(5,N = 684) = 306.3$, $p < 0.001$, $\eta^2 = 0.44$). As for laundry patterns, for convenience we will refer

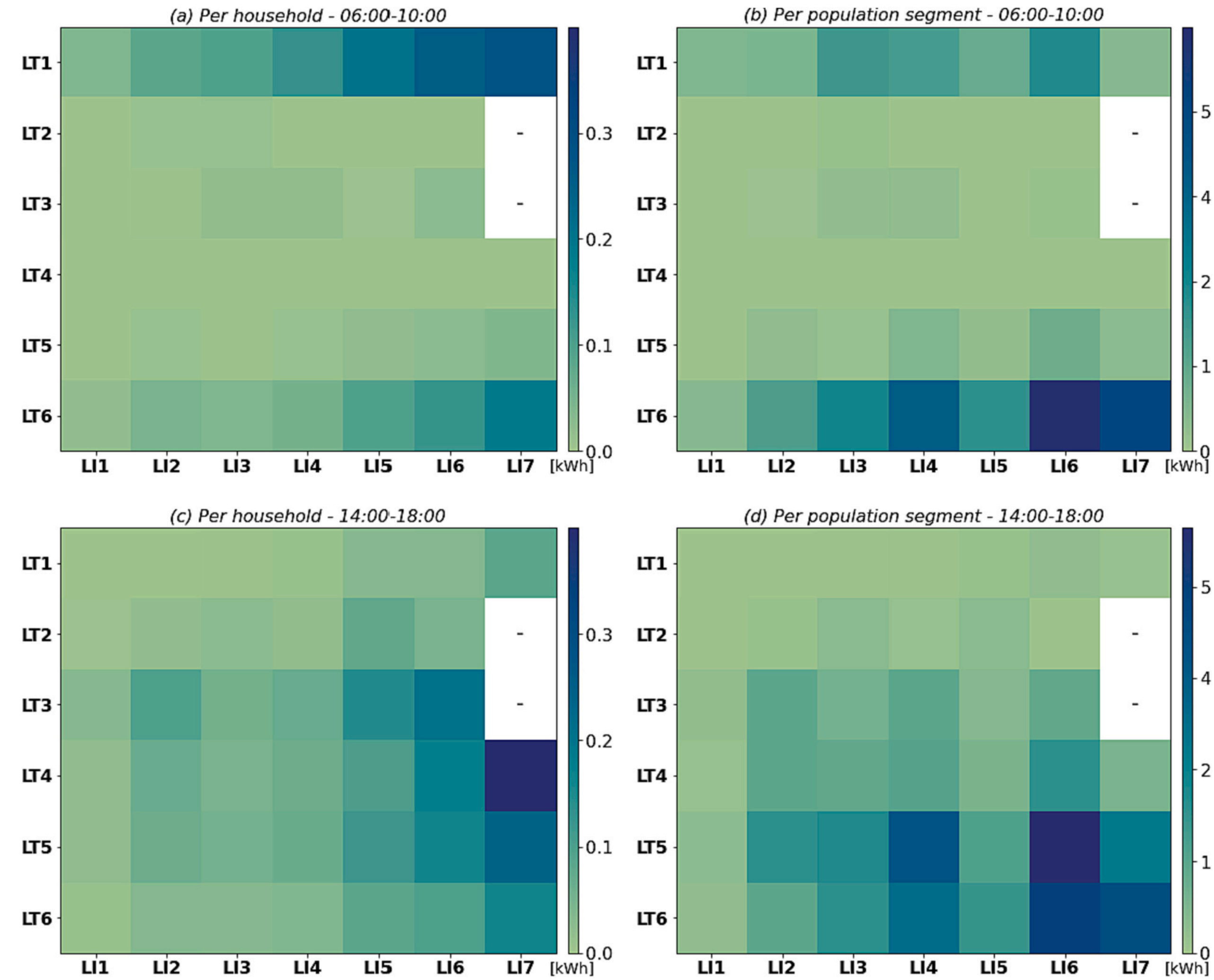

Fig. 2. Estimated laundry energy consumption per household and population segment, i.e. weighted by the segment's share over 1000 households, during the morning (06:00–10:00) and afternoon (14,00–18:00) hours.

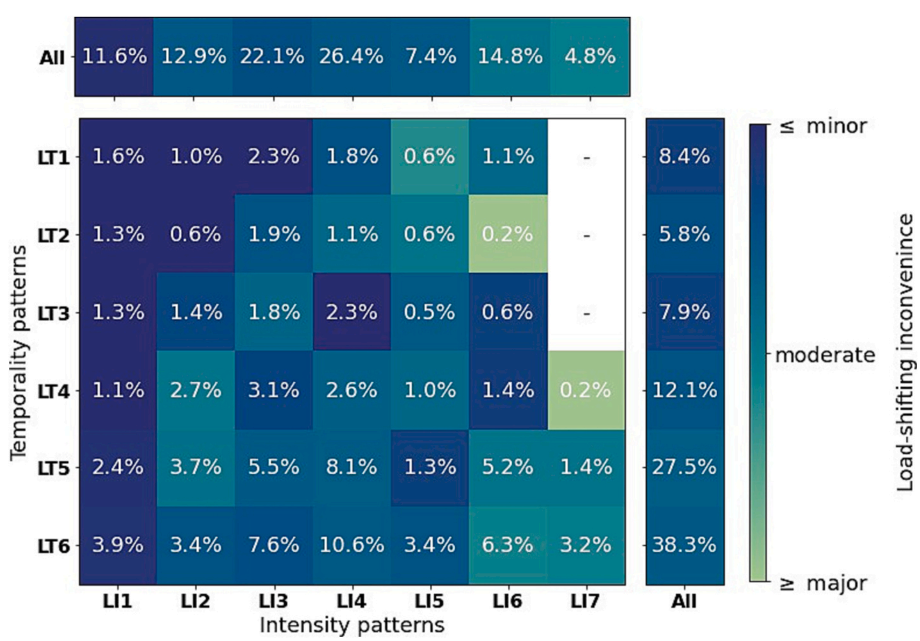

Fig. 3. Heatmap of perceived inconvenience for a wash cycle delay of up to 6 h. Each cell is defined by a combination of two clusters, and its size relative to the total sample is reported as a percentage within it. Average values per single cluster are reported in the column and row (All). The percentage values in each cell refer to the share of the segment in the sample.

to these patterns using the acronym DI (Dishwashing Intensity).

In Table 8, we present a concise overview of the identified dishwashing intensity patterns, together with their respective washing frequencies, energy intensity per washing cycle, and population shares. These patterns can be sorted into four levels based on their average washing frequencies: low (DI1), medium-low (DI2 and DI3), medium-high (DI5), and high (DI6). It is noteworthy that, when compared to laundry, the dishwashing intensity clusters exhibit a lesser degree of variation in terms of intensity per single washing cycle. For a more in-depth understanding of each variable's distribution within each cluster, please refer to Appendix (see Fig. 10), where we have visualised the results using boxplots.

Regarding the clustering of dishwashing temporality patterns, we chose three clusters. Iteratively, we also tested a larger number of clusters, but as the dendrogram graphs show (see Figs. 6 and 7 in Appendix), a larger number of clusters implied fragmentation of the sample into very small clusters, considered of little interest for analysis. The selected clusters proved to be in 89.5 % agreement with the classification provided by the k-means clustering, and well segmented according to all clustering dimensions: *morning* (H(2,N = 630) = 47.6, $p < 0.001$, $\eta^2 = 0.073$), *midday* (H(2,N = 630) = 188.7, $p < 0.001$, $\eta^2 = 0.298$), *afternoon* (H(2,N = 630) = 79. 8, $p < 0.001$, $\eta^2 = 0.124$), *evening* (H(2,N = 630) = 284.4, p < 0.001, $\eta^2 = 0.450$), *night* (H(2,N = 630) = 107.8, p < 0.001, $\eta^2 = 0.169$). To ease the presentation of results, we refer to these clusters by the acronym DT (Dishwashing Temporality).

In Table 9, we outline distinct temporality patterns associated with dishwashing behaviour. Notably, most of the households (77 %; N = 490) fall into the DT1 cluster, showcasing a lack of clear routine. Similarly, DT3, the second-largest cluster comprising 16 % of households, also demonstrates a non-routinised dishwashing pattern, albeit with a subtle inclination towards washing earlier in the day. In contrast, DT2 represents a smaller but distinctive cluster (5 %; N = 33), characterised by a consistent tendency of its members to start the dishwasher during the evening hours. These results shed light on the temporal dynamics of dishwashing habits within households, revealing a predominant tendency towards non-routine behaviour, with a notable exception in the form of the routinised evening washers observed in the smaller DT2 cluster.

Table 8
Dishwashing intensity patterns.

ID	Description	Frequency [Wash/week]	Energy [kWh/wash]	Share [%]
DI1	**Low Frequency**. Members in this cluster wash approximately once a week, with a wash cycle energy intensity matching the overall sample average.	0.9	1.1	19
DI2	**Low to Medium Frequency, Low Energy Intensity**. This cluster reports washing twice a week, with an average energy intensity per wash cycle lower than the entire sample.	1.8	0.9	15
DI3	**Low to Medium Frequency, High Energy Intensity**. Members in this cluster wash twice a week, but with an average energy intensity per wash cycle higher than the overall sample.	1.8	1.3	3
DI4	**Low to Medium Frequency, Average Energy Intensity**. This cluster, with a twice-a-week washing frequency, exhibits an average energy intensity per wash cycle that aligns with the overall sample. With (N = 251) cases, this is the largest dishwashing intensity cluster.	2.5	1.0	29
DI5	**Medium to High Frequency, Variable Intensity**. Respondents in this cluster wash around five times a week, with a similar average washing intensity as the entire sample, but notable variability between cases.	4.5	1.0	19
DI6	**High Wash Frequency**. Members in this cluster use the dishwasher at least seven times a week.	7.1	1.0	11
	Whole sample	3.0	1.0	100

4.2.2. Characterising dishwashing patterns

As for the laundry patterns, multinomial logistic models have proved to have a good fit for both dishwashing intensity (Model 3: $\chi^2(190, N = 599) = 381.7$, $p < 0.001$, $R^2_{MFH} = 0.173$) and temporality (Model 4: $\chi^2(76, N = 557) = 137.1$, $p < 0.001$, $R^2_{MFH} = 134$) patterns. In Table 10, we report the coefficients, standard deviation and significance of regression models.

Model 3 results are reported using DI4 as a reference, which has a frequency and energy intensity of washing close to the mean of the whole sample. The lowest wash frequency cluster (DI1) appears to be less associated with home-workers than DI4. Among the low-to-medium wash frequency clusters, DI2 stands out for being composed of smaller households. However, no other significantly relevant factors emerge to explain why it has a slightly lower wash frequency and wash temperature than DI4. Compared to DI4, DI3 is also characterised by smaller households that tend to live in terraced houses rather than flats and to be (co)owners. The comparison with the clusters with a higher washing frequency shows that both DI5 and DI6 are characterised by larger households. In the case of DI5, it is possible to see that this cluster is more associated with respondents under the age of 65, who are neither full-time nor part-time workers, and have a high salary. They also indicated less frequently that time availability is an issue in activating the dishwasher. While for DI6, besides household size, two social-psychological factors (i.e. *Effort* and *Comfort attitude*) prove to be significant factors. As observed for laundry intensity patterns, neither environmental nor economic attitudes proved to be a significant distinguishing factor between DI4 and the other patterns.

For Model 4, we took DT1, that is, the cluster associated with no specific preference for washing hours, as a contrast. Compared with

Table 9
Dishwashing temporality patterns. Abbreviations: (MO) Morning; (MI) Midday; (AF) Afternoon; (EV) Evening; (NI) Night.

ID	Description	MO [%]	MI [%]	AF [%]	EV [%]	NI [%]	Share [%]
DT1	**Non-Routinised Washers (Later Wash Tendency)**. This is the dominant cluster and it is associated to no particular routinised behaviour. In general, the members of this cluster tend to prefer washing in the afternoon and evening over morning and midday.	10	19	28	32	12	77
DT2	**Highly-Routinised Evening Washers**. This group, the smallest cluster, is highly routinised, showing a clear preference for using the dishwasher in the evening.	4	3	1	92	0	5
DT3	**Non-Routinised Washers (Earlier Wash Tendency)**. It consists of respondents with no specific routinised behaviours. They tend to wash earlier during the day and avoid evening and night washes, in contrast to cluster DT1.	26	41	26	7	0	16
	Whole sample	12	22	26	31	9	100

Table 10
Multinomial logistic regression coefficients and standard deviations of predictors of dishwashing intensity (Ref. = DI4) and temporality (Ref. = DT1) pattern membership. Results statistically significant at: † 10 % level; * 5 % level; ** 1 % level; *** 0.1 % level.

	Model 3: dishwashing intensity					Model 4: dishwashing temporality	
	DI1	DI2	DI3	DI5	DI6	DT2	DT3
Constant	2.84 (1.74)	−0.71 (1.73)	−2.65 (3.57)	−4.56** (1.66)	−6.33*** (1.86)	−2.34 (2.55)	0.18 (1.48)
Household size	−1.11 (1.11)	−1.21* (0.61)	−2.06† (1.17)	1.33** (0.50)	2.11*** (0.60)	−0.06 (0.88)	−0.89 (0.51)
Household size^2	−0.07 (0.31)	0.12 (0.12)	0.24 (0.23)	−0.14† (0.08)	−0.24** (0.09)	0.01 (0.16)	0.12 (0.10)
Age (<30 y/o)							
30–64 y/o	−0.07 (0.43)	0.75 (0.55)	0.25 (1.12)	0.29 (0.41)	0.82 (0.53)	0.61 (0.89)	0.37 (0.52)
≥65 y/o	−0.23 (0.55)	0.23 (0.65)	−0.81 (1.37)	−1.19* (0.54)	−0.12 (0.70)	2.10* (1.07)	1.18 (0.58)
Gender (female)							
Male	−0.20 (0.29)	0.08 (0.30)	−0.38 (0.61)	0.25 (0.28)	−0.04 (0.34)	−0.34 (0.45)	0.12 (0.28)
Tenure (tenant)							
(Co)owner	0.01 (0.35)	0.23 (0.35)	1.59* (0.76)	0.30 (0.33)	−0.48 (0.39)	0.17 (0.54)	0.55 (0.35)
Accommodation (flat)							
(Semi)detached	0.30 (0.39)	0.24 (0.41)	0.88 (0.81)	−0.03 (0.36)	0.18 (0.43)	0.06 (0.61)	−0.24 (0.37)
Terraced	−0.80 (0.72)	0.97† (0.52)	2.31** (0.87)	0.40 (0.50)	0.56 (0.60)	−0.86 (0.88)	−0.06 (0.49)
Location (<20k hab.)							
20k–100k	−0.21 (0.36)	0.22 (0.38)	0.40 (0.70)	−0.30 (0.35)	−0.29 (0.42)	−0.79 (0.65)	0.06 (0.33)
>100k	0.34 (0.35)	0.47 (0.38)	0.62 (0.76)	−0.26 (0.34)	−0.34 (0.41)	0.62 (0.55)	−0.21 (0.34)
University (no)							
Yes	−0.37 (0.31)	0.03 (0.31)	−1.33* (0.68)	−0.36 (0.29)	0.13 (0.35)	−1.82*** (0.52)	−0.24 (0.30)
Employment (full-time)							
Part-time	−0.19 (0.49)	−0.15 (0.47)	−0.50 (0.98)	−0.23 (0.43)	0.20 (0.45)	0.47 (0.64)	0.29 (0.51)
Other	0.02 (0.46)	0.26 (0.49)	0.06 (0.97)	1.01* (0.44)	0.26 (0.54)	−0.88 (0.78)	0.75† (0.42)
Home-office (no)							
Yes	−1.35** (0.50)	−0.04 (0.40)	−0.75 (0.94)	0.01 (0.37)	0.29 (0.40)	−0.02 (0.58)	−0.34 (0.50)
Income (<1300k€)							
1300–1699€	−0.44 (0.56)	−0.84 (0.62)	−0.41 (1.68)	1.59† (0.82)	0.48 (0.77)	−1.75 (1.33)	−1.32 (0.55)
1700–2599€	−0.01 (0.51)	−0.76 (0.54)	1.21 (1.32)	1.12 (0.76)	0.15 (0.66)	−0.14 (0.93)	−0.71 (0.45)
2600–3599€	0.22 (0.57)	−0.03 (0.56)	1.60 (1.31)	1.77* (0.76)	0.11 (0.67)	−0.23 (0.96)	−1.26 (0.51)
>3600€	0.05 (0.60)	−0.47 (0.60)	0.92 (1.41)	1.68* (0.76)	−0.06 (0.68)	0.92 (0.97)	−1.04 (0.54)
n.a.	−1.56† (0.92)	−0.45 (0.70)	1.64 (1.45)	1.11 (0.85)	−1.05 (1.01)	0.46 (1.19)	−0.33 (0.60)
PV system (no)							
Yes	0.36 (0.42)	−0.66 (0.52)	−1.33 (1.21)	0.20 (0.39)	0.06 (0.48)	−0.22 (0.67)	−0.11 (0.41)
Start-delay use (no)							
Yes	−0.06 (0.45)	−0.41 (0.52)	−0.83 (1.17)	−1.14* (0.48)	−0.13 (0.47)	0.01 (0.72)	−0.23 (0.46)
Prompts (no)							
Daytime constr.	−0.04 (0.40)	0.43 (0.41)	1.12 (0.73)	0.35 (0.39)	0.42 (0.45)	−1.16† (0.70)	−0.41 (0.38)
Free time before	−0.48 (0.33)	−0.25 (0.35)	−1.72† (0.93)	−0.66* (0.33)	−0.75† (0.39)	−0.81 (0.62)	−0.68 (0.36)
Fixed day	0.18 (0.45)	0.48 (0.47)	0.29 (0.93)	0.24 (0.45)	−0.03 (0.53)	0.52 (0.62)	0.25 (0.43)
Recursive	−0.31 (0.30)	0.10 (0.33)	−0.41 (0.66)	−0.09 (0.29)	−0.11 (0.34)	−0.76 (0.54)	−0.76 (0.32)
Occasional	0.02 (0.40)	0.05 (0.44)	1.28 (0.78)	0.38 (0.38)	−0.33 (0.51)	−1.37† (0.82)	−0.76 (0.45)
No reason	−1.20† (0.64)	0.08 (0.56)	−0.07 (1.02)	−1.03 (0.67)	−0.63 (0.75)	0.05 (0.80)	−0.48 (0.54)
Social-psychological							
EconAtt	0.05 (0.16)	−0.00 (0.17)	0.50 (0.39)	−0.22 (0.17)	−0.23 (0.19)	0.30 (0.25)	−0.01 (0.16)
EnvAttEnergy	0.12 (0.16)	−0.17 (0.18)	0.01 (0.33)	−0.27 (0.17)	0.19 (0.19)	0.79** (0.27)	0.05 (0.16)
EnvAttGeneric	−0.04 (0.16)	−0.19 (0.16)	−0.13 (0.35)	0.03 (0.14)	0.19 (0.17)	−0.66* (0.28)	0.02 (0.14)
Effort	−0.09 (0.20)	−0.02 (0.21)	−0.56 (0.38)	−0.23 (0.18)	−0.48* (0.21)	0.14 (0.30)	−0.05 (0.18)
ComfAtt	−0.63* (0.31)	−0.59† (0.33)	−1.22† (0.68)	−0.43 (0.32)	−0.80* (0.38)	−1.12* (0.52)	−0.41 (0.31)
PerNorms	0.14 (0.22)	0.23 (0.23)	0.73 (0.48)	0.10 (0.21)	−0.00 (0.25)	−0.20 (0.34)	−0.17 (0.22)
SocNorms	0.09 (0.17)	0.22 (0.17)	−0.21 (0.38)	−0.32† (0.17)	−0.25 (0.19)	0.18 (0.23)	0.39 (0.16)
EneLit	0.53* (0.23)	0.41† (0.24)	0.24 (0.48)	0.11 (0.22)	0.50† (0.26)	0.21 (0.35)	0.19 (0.22)
SelfEff	−0.36† (0.21)	−0.18 (0.22)	−0.41 (0.41)	−0.39† (0.20)	0.00 (0.25)	−0.33 (0.35)	0.02 (0.21)
Justification	0.14 (0.15)	−0.04 (0.15)	0.21 (0.32)	−0.03 (0.13)	0.03 (0.15)	−0.26 (0.22)	−0.07 (0.14)
	N = 599					N = 557	
	$R^2_{MFH} = 0.173$					$R^2_{MFH} = 0.134$	

DT1, households with preference for washing in the evening hours (DT2) tend to have a higher level of education and to be older, whereas households that tend to wash earlier in the day, but without specific routines (DT3), are generally smaller and older. They are also more associated with respondents who are not working, living in lower income households, and more rarely indicated starting the dishwasher on a weekly or daily schedule.

4.2.3. Load-shifting potential across dishwashing patterns

Fig. 4 shows the estimated morning and afternoon energy consumption per individual household and population segment. Regarding morning energy consumption at the individual household level, respondents who indicated a low preference for morning hours (i.e. DT3) and a high washing frequency have on average a higher energy consumption during these hours (see Fig. 4.a). However, since these segments cover a small percentage of the entire population, they contribute little to morning energy consumption. As far as energy consumption in the afternoon hours is concerned, at the level of individual households, the highest consumption is estimated for the DT1 or DT3 pattern (see Fig. 4.c). But, as in the previous case, the greatest potential lies in cases belonging to DT1, due to its greater spread in the population (see Fig. 4.d, c). But, as in the previous case, the greatest potential lies in cases belonging to DT1, due to its greater spread in the population (see Fig. 4.d).

Fig. 5 shows in the form of a heat map the readiness of different segments of the sample to delay dishwashing up to a maximum of 6 h, automatically. As already reported for laundry, each cell is associated with the sample corresponding to the combination of a pair of dishwashing intensity and temporality patterns, whose spread over the sample is reported as a percentage value directly in the corresponding cell. The Kruskal-Wallis test shows that the perceived inconvenience of

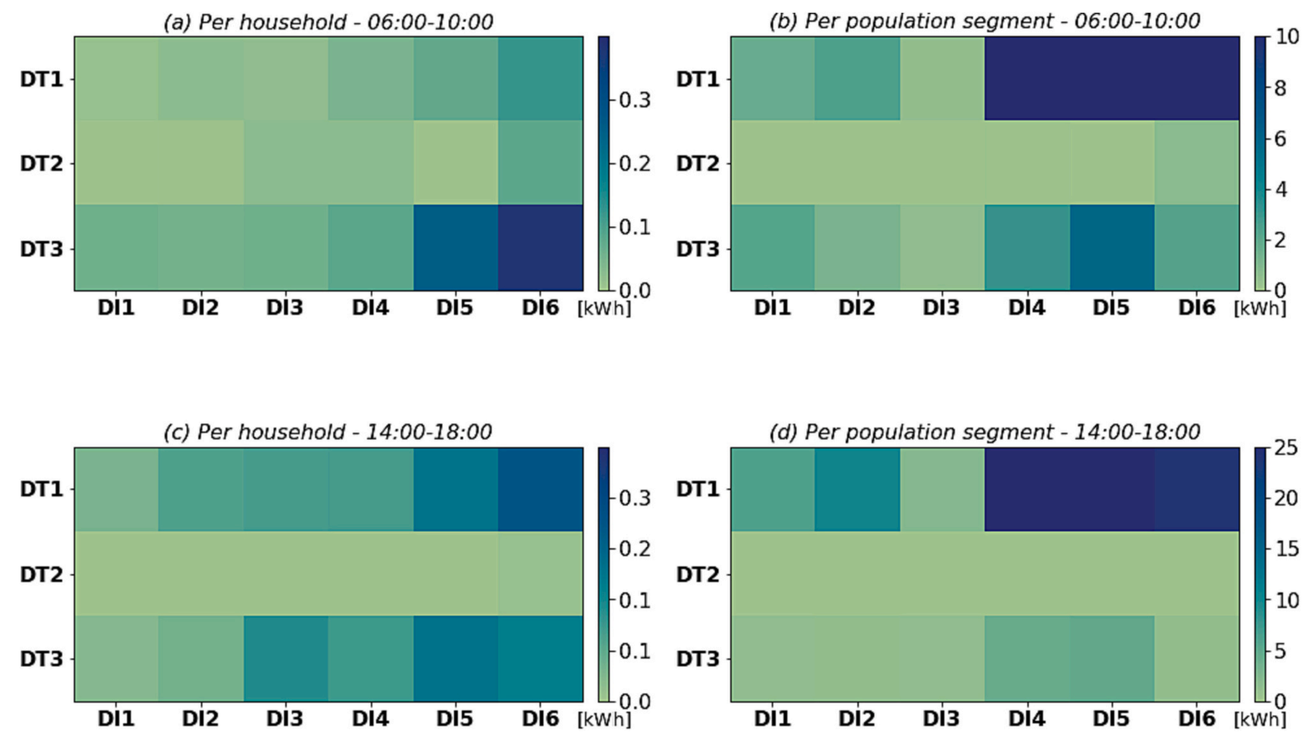

Fig. 4. Estimated dish-washing energy consumption per household and population segment, i.e. weighted by the segment's share over 1000 households, during the morning (06:00–10:00) and afternoon (14:00–18:00) hours.

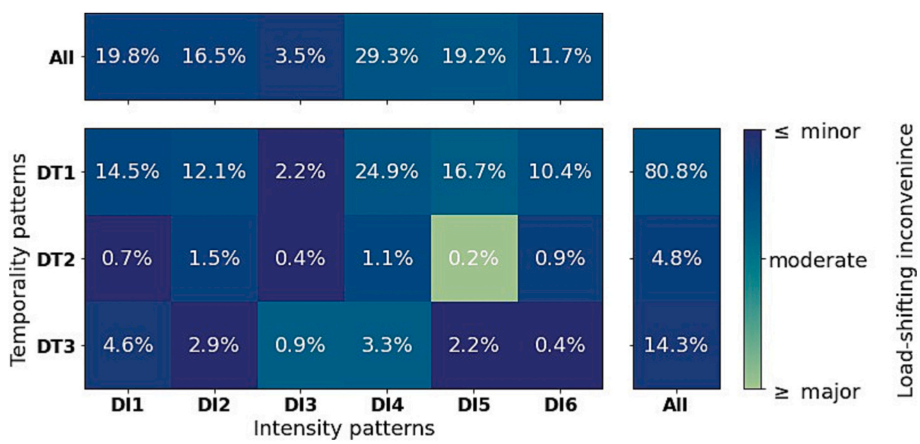

Fig. 5. Heatmap of perceived inconvenience for a wash cycle delay of up to 6 h. Each cell is defined by a combination of two clusters, and its size relative to the total sample is reported as a percentage within it. Average values per single cluster are reported in the column and row (All). The percentage values in each cell refer to the share of the segment in the sample.

load-shifting is significantly different among the clusters of dishwashing intensity, with a small effect size (H(6, N = 684) = 13.1, $p = 0.022$, $\eta^2 = 0.015$), while it is not significantly different among the three clusters related to temporality (H(3, N = 630) = 4.1, $p = 0.130$, $\eta^2 = 0.004$).

5. Discussion

In the previous sections, we have shown, from a methodological and practical point of view, how self-reported data on wet appliance usage can jointly explore the intensity and temporality of energy use within and across households, identify its determinants, and draw targeted implications for final energy consumption, and for its flexibilization. Below, we discuss the results in relation to three questions, each associated with one of the research objectives (see Section 1). We will conclude this section discussing limitations and prospects for future research.

5.1. *Scattered and indistinguishable variability or common patterns of appliance usage?*

In this study, we show that, through an iterative process of fine-tuning a clustering procedure based on self-reported data, it is possible to "order" the diversity of performing dishwashing and laundry habits into a set of distinct patterns. This is a crucial step and an efficient methodology compared to the reductionist view of solely characterising energy demand by considering the "average consumer" or socio-demographic segmentation typical of techno-economic energy modelling studies. Although the clustering procedure followed a trial-and-error approach and was necessarily conditioned by the subjectivity of feature selection and the choice of the number of clusters, it nevertheless provides new methodological insights. Indeed, a characterisation based on a larger number of practice-related parameters and tasks is desirable [74], but we did not observe meaningful results when we fed the clustering analysis with all available variables. This may be due to methodological reasons (e.g. the inadequacy of the clustering algorithm and difficult comparability of variables) or simply the absence of comprehensive patterns. As we have shown, a possible alternative is to divide the variables into two thematic areas (i.e. intensity and temporality) while conducting two separate clustering analyses. The results provided a clearer and empirically-based picture of the laundry and dishwashing patterns complementing TUD-based studies on the intensity (e.g. TV watching [98]) and temporality [25,78] of daily activities, which have shown to have a modest predictive power for the electricity use of some appliances [99]. Furthermore, the proposed approach allows us to analyse intensity and temporality of activities on the same sample and thus to jointly map and return a comprehensive picture of how the volume and temporality of energy consumption varies in the population. The advantages of this are discussed further below (see Section 5.3).

Beyond the methodological contribution, the patterns identified provide new insights into the understanding and quantitative characterisation of household habits. First, they provide an important empirical basis for studies aimed at assessing the impact of consumer behaviour on energy consumption by allowing validation against a real-world context, which was hitherto precluded in studies based on best guesses [41,100]. Second, they emphasise relationships among habit elements that are typically neglected. For example, our results confirm what has been observed in Hess et al. [101] in relation to the variability of washing temperature in the population, further showing that this variability is more pronounced among patterns with low to medium washing frequency. This may be due to the fact that, as washing frequency increases, there is an opportunity to sort laundry items (e.g. delicate, white, synthetics) and thus to choose the most appropriate program. Whereas at lower wash frequencies, where laundry is usually mixed, conventions are more important. Moreover, while TUD-based analyses provided insights into the phenomena of duration, synchronicity, and sequence of activities and how these may shape the load and particularly the peak periods [24,102], here our findings highlight an additional aspect, namely the periodicity or rhythm of activities [103]. In particular, a clear dichotomy emerges between regular and non-regular temporality patterns. As discussed in more detail below, the more or less routinised nature of activity performance is associated with different segments of the population, and plays a non-negligible role in shaping energy demand and its possible reconfiguration over time.

5.2. Determinants of appliance usage patterns: a few key factors or multiple distributed influences?

To provide new insights to the epistemological debate that characterises engineering, social-psychological and social practice approaches to energy consumption, we showed how different factors contribute to explaining household's membership in the different patterns of appliance usage. To this end, we considered a wide range of explanatory factors (e.g. socio-demographic, technological, psychological, spatio-temporal) and demonstrated through multinomial logistic regression models that different combinations of factors contribute to the formation of the intensity and temporality patterns for laundry and dishwashing.

Among the factors shown to be most significant were, as expected, household size (both the linear and quadratic factors) in relation to intensity patterns, and age and employment status in relation to temporality patterns. However, results from logistic regression models using solely a set of socio-demographic variables showed poor fit in relation to both temporality and intensity of habits. As noted in Torriti and Yunusov [102] studying activity patterns during peak hours, this confirms that the analysis of household activities and energy demand in general cannot rely solely on socio-demographic factors. First, the ownership of technologies and their technical characteristics (e.g. year of adoption and smart functionality) contribute to the construction of the intensity and temporality of energy end uses. For instance, it emerged that the availability of a dryer and the presence of a PV system influence the frequency and choice of washing schedule towards more intensive habits, as the habits may become less time-consuming and energy is free at certain times of the day, giving rise to a phenomenon known as solar rebound [104]. Looking beyond the case of laundry and dishwashing habits, this challenges the typical modelling assumption that user behaviour is technology-independent (e.g. thermostat settings do not change when moving from gas-boiler-based to heat-pump-based heating) and highlights the need for more attention to the opportunities and obstacles for change formed by the co-presence of end-users and material artefacts and their interrelationship, e.g. through theories of 'domestication' [105], 'social learning' [106], or 'material participation' [107]. Second, socio-psychological factors, such as *comfort attitude*, *effort*, and *justification behaviour*, influence the frequency and choice of washing programme in complex ways, whereas environmental and economic attitudes do not prove to be significant. On the one hand, this confirms that the social-psychological dimension is an important component of household habits, but as its contribution is pattern-specific, a better understanding of the interaction between social-psychological factors and the other elements that constitute the habits is needed. For example, for those patterns that have been found to be more sensitive to comfort and effort, it may be more effective to develop automated demand management solutions that take into account the specificity of the socio-material arrangements in place. Whereas for other patterns, sacrificing one's comfort in favour of environmental or altruistic values may prove to be a more appropriate lever. On the other hand, the fact that environmental attitudes turn out not to be significant in determining intensity patterns confirms the gap between intentions and actual behaviour in the sphere of everyday, routinised behaviour, calling into question the effectiveness of generalist environmental awareness campaigns aimed at, for example, energy saving. Third, as noted in Yates and Evans [74], the importance of the triggers, stimuli, and timing of habits (e.g. time availability, recurring days, weather conditions) confirms how relevant the rhythms of home life (how laundry fits into the other time demands of the household) are in determining when and how habits are performed. This, however, does not apply equally to dishwashing and laundry habits, since the latter are less routinised and responsive to opportunistic 'time gaps', as also observed in Nicholls and Strengers [73]. As further discussed below (see Section 5.3), even for patterns where triggers and stimuli are more constraining, there is still some room for load-shifting interventions. However, if the energy system required greater adjustments in energy demand, the results indicate that more structural interventions are needed, aimed at changing the set of triggers and stimuli at the household and societal levels (e.g. school shuttle services, flexible work schedules or smart-working days), rather than focusing solely on the individual.

Apart from detailing the multiplicity of factors and complex relationships that determine the intensity and temporality of laundry and dishwashing habits, the results demonstrate the need for a change in perspective. Indeed, if household habits are the result of complex and distributed elements, any segmentation approach based on a limited set of factors, whether socio-demographic, psychological or technological, cannot provide a detailed and accurate picture of the diversity of performance of habits in the population. With this in mind, we argue that current energy modelling and policy evaluation methods would benefit from a pattern-based perspective, tailoring the analysis to the performance of the habits itself rather than a segmentation derived from individual disciplines and perspectives.

5.3. Are energy-intensive patterns just as ready to load-shift?

To illustrate how a pattern-based perspective can contribute to a better understanding of energy consumption and flexibility, we estimated how perceived inconveniences related to load-shifting and energy consumption during key periods (i.e. 6:00–10:00 a.m. for consumption from PV generation and 2:00–6:00 p.m. for grid congestion relief) vary among patterns. First, clear differences emerge in the perceived inconvenience of load-shifting among the patterns. For example, patterns with higher washing frequency perceive load-shifting as more inconvenient. This may be because a higher frequency of washing is associated with a faster pace of domestic life; what is referred to in Southerton [103] as tempo. Therefore, delaying a washing event may represent a slowdown of the activity, creating possible conflicts with subsequent occurrences and thus changing the dynamics of periodicity, duration, synchronisation, and sequence that characterise the time and mode of execution of the activity and its related-tasks (e.g. unloading, drying, ironing).

Second, by intersecting the temporal and intensity patterns, we estimated who consumes, how much, and when. Through this mapping of energy consumption, we highlighted where the greatest potential lies—in terms of kWh per individual or population segment—to synchronise consumption with PV generation or to alleviate grid congestion. The results show that the greatest potential is not necessarily found among the most energy-intensive households and that the temporal characterisation of habits plays a non-secondary role. This complements what has been observed through the analysis of time-use data (TUD), providing an empirical-quantitative basis for the assessment of effects of inequality and unfairness in relation to the introduction of time-of-use (TOU) tariffs (e.g. the inequitable financial burden on caregivers of children [108] and distributional effects based on regional differences and household composition [109]). Moreover, they advocate the need to make DSM programs highly targeted to enable end users to provide the services best suited to their rhythm of domestic life [110].

Finally, when comparing the mapping of readiness to load-shifting with that of energy consumption, a clear mismatch emerges, i.e. the laundry patterns that are more energy-intensive during flexibility-relevant periods are generally those that perceive load-shifting as more inconvenient. On the one hand, this confirms that dishwashing may be more suitable for the provision of flexibility services compared to laundry. On the other hand, it points to a possible cause of inaccurate estimation if the analysis of flexibility potential is carried out by considering the consumption profile and readiness for flexibility at the average population level, providing further support for Parrish et al.'s argument that modelling assumptions on demand flexibility are typically over-optimistic [12].

5.4. Limitations and prospects for future research

Our study provides valuable insights into understanding variations in energy demand across households, particularly in terms of energy intensity and the timing of appliance usage. However, it has certain limitations. Firstly, our reliance on survey data introduces potential biases from self-reporting and response categorisation errors [111]. To address these challenges, different solutions could be explored, such as smart meter data coupled with Non Intrusive Load Monitoring (NILM) algorithms [112], smart plug measurements, or data from smart and domotic devices. In this regard, however, it is important to note that researchers have demonstrated value and complementarity in both monitored and self-reported data, showing that one does not replace the other when both technical and human interactions need to be understood [113,114]. Moreover, it is important to recognise that computer-administered surveys, despite incurring costs for implementation, recruitment, and distribution, remain a more cost-effective option when compared to load-monitoring campaigns as they do not need any hardware installation (e.g. smart plugs) on the user side. Therefore, we recommend a careful evaluation of the costs, advantages and disadvantages of different data sources in order to guide the choice of the most appropriate data collection method according to the purpose of analysis.

Second, our current methodology involves an ad-hoc selection of variables and the use of Ward's hierarchical clustering, tested against k-means clustering. To enhance the robustness of our analysis, we recommend exploring alternative clustering methods, such as density-based or model-based techniques (e.g., decision trees, DBSCAN, Gaussian mixture models) [115]. This systematic exploration can provide a deeper understanding of household appliance usage patterns, accommodating different data types and structures.

Finally, our research primarily adopts a quantitative approach to identify appliance usage patterns and assess their correlation to various factors, such as socio-demographic attributes, technical characteristics of devices, social-psychological factors, and spatio-temporal prompts. However, it is essential to recognise the limitations of this quantitative focus in capturing the qualitative aspects inherent in daily practices. Everyday practices involve materials, competences, and social and symbolic meanings [30]. While attempts have been made to incorporate these qualitative dimensions into quantitative surveys [81], the diversity of factors suggests that a purely quantitative survey is insufficient. Therefore, our approach could be complemented with interviews to gain a deeper understanding of participant's daily practices and identify potential intervention points that quantitative metrics may overlook [116].

6. Conclusion

To ensure secure and reliable operation of a highly decarbonised and electrified energy system, DSM programmes emerge as a promising solution. In this article, we introduce and operationalize a new perspective to enhance our comprehension of energy demand and flexibility potential. This approach considers not only the volume but also the timing and distribution of energy demand across the population. Unlike conventional methods that rely on socio-economic and social-psychological segments to characterise energy demand heterogeneity, our approach centres on the concept of appliance usage patterns—common variants frequently observed in the population. The core idea is to delve into the intricacies of energy consumption by scrutinising how people use their appliances, identifying recurring patterns within the population, and exploring the various factors influencing such patterns. By embracing this perspective, our goal is to shift the research focus towards an integrated understanding of energy consumption. Specifically, we contend that appliance usage patterns can inform the development of socio-technical engineering-based models and provide a valuable quantitative basis for testing hypotheses in the social sciences, ultimately offering a more detailed, holistic, and DSM-relevant portrayal of the diversity of energy consumption across households.

We illustrated and operationalized this perspective by collecting and analysing survey data on appliance usage (e.g. frequency, time of day and mode of use) as a tangible and quantifiable proxy for how and when laundry and dishwashing activities are performed. First, we demonstrated that the diversity of these activities among households can be structured into a number of distinct patterns of intensity and temporality by applying exploratory cluster analyses. This suggests that DSM interventions, aimed at both energy efficiency and flexibility, should consider the different aspects of the activities and their interdependence, trying to change the pattern in a composite and coherent way rather than individual aspects (e.g. reducing solely the washing temperature).

Second, using multinomial logistic regression, we found that pattern membership is the result of complex and multiple influences. This challenges traditional modelling approaches and policy interventions based on a limited set of factors (e.g. socio-economic or social-psychological segments) in favour of a more holistic and interdisciplinary approach. In particular, since patterns embody these multiple and complex influences, we suggest that pattern-tailored interventions might be a more effective and practical approach.

Third, we showed that the intersection of intensity and temporality patterns provides a detailed and highly heterogeneous picture of household energy consumption patterns. Within this heterogeneity, it is important to highlight that a small portion of the population is responsible for much of the estimated energy consumption for laundry and dishwashing activities in the morning and afternoon hours, i.e. those relevant for increasing self-consumption from PV or relieving grid congestion through load-shifting. Therefore, we suggest that system operators, aiming to leverage the potential of DSM in their user portfolios, embrace the proposed pattern-oriented approach. This approach facilitates the time-sensitive mapping of flexibility potential across the population and provides guidance for designing DSM solutions in a more targeted manner.

At the same time, however, we have shown through Kruskal-Wallis tests that households belonging to different patterns perceive the inconvenience of load-shifting in a statistically different way, and we have found that households with higher energy consumption in the above-mentioned time slots tend to show less readiness for load-shifting. This casts doubt on the actual potential for flexibility and indicates that the DSM potential will not be easily accessible if system operators, in addition to identifying the households with the highest energy consumption, do not develop tailored methods to mobilise their flexibility.

In conclusion, building on the approach proposed in this study, we encourage social science studies to investigate the existence of patterns among the different activities not considered here (e.g. clothes drying, space heating and electric vehicle charging), exploring the dependencies and coexistence of patterns, and unravelling the complex web of influences (e.g. demographic, psychological, material, spatial and temporal) that shape their form and trigger change. Moreover, rather than relying on socio-economic segmentation approaches, which assume that everyone in a particular group behaves the same, we suggest that new modelling research on energy demand and flexibility should characterise each household through a set of appliance usage patterns and accounts for how they are likely to change in different ways over time. This shift could enable new methods of interdisciplinary energy demand research and open new perspectives on the analysis of consumer response to (non)price-based DSM mechanisms, which would provide a more realistic understanding and assessment of the consumer behaviour adaptation over time, beyond utility maximisation approaches.

CRediT authorship contribution statement

Matteo Barsanti: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing, Project administration. **Selin Yilmaz:** Supervision, Writing – original draft, Writing – review & editing. **Claudia R. Binder:** Funding acquisition, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Matteo Barsanti reports financial support was provided by Swiss National Science Foundation (SNSF).

Data availability

The data that has been used is confidential.

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Appendix A

Table 11
Psychometric items and constructs included in Block E.

Item (Abbreviation)	Scale	M	SD	Ref.
Economic attitude (EconAtt)				
1. I primarily pay attention to energy consumption in the household because of financial reasons.	6	4.76	1.21	[84, 56]
2. When purchasing household appliances I pay attention to energy consumption because of the running costs.	6	5.02	1.10	[84, 56]
Environmental attitude – energy related (EnvAttEnergy)				
1. I primarily pay attention to energy consumption in the household because of environmental concerns in general.	6	4.33	1.35	[84, 56]
2. When purchasing household appliances, I pay attention to energy consumption because of the environmental problem.	6	4.78	1.25	[84, 56]
Environmental attitude – generic (EnvAttGeneric)				
1. If we carry on as we have done up to now, we will be heading for an environmental disaster.	6	4.53	1.39	[85, 86]
2. In my opinion, the importance of the environmental problem is greatly exaggerated by many environmentalists.	6	2.77	1.54	[85, 86]
3. Environmental protection measures should be enforced even if they cause jobs to be lost.	6	3.49	1.42	[85, 86]
4. For the benefit of the environment, we should all be ready to reduce our current standard of living.	6	4.26	1.35	[85, 86]
Energy literacy (EneLit)				
1. I know the areas of my household with the highest energy consumption and, accordingly, I can/could behave energy consciously without any problems.	6	4.30	1.14	[84]
2. I am confident that I am able to make an energy-conscious decision when buying household appliances or cars.	6	4.87	0.96	[84]

(continued on next page)

Table 11 (*continued*)

Item (Abbreviation)	Scale	M	SD	Ref.
Self-efficacy (SelEff)				
1. The many small efforts I make to behave in an energy conscious manner add up, too, and can make a change with regard to general energy consumption.	6	4.78	1.05	[84]
2. I believe that my personal behaviour can bring about a positive change in the environment.	6	4.40	1.23	[85]
Social norms (SocNorms)				
1. In general, people close to me expect me to behave in an energy conscious manner.	6	3.91	1.37	[85]
2. People who are important to me tend to behave in an energy conscious manner.	6	4.18	1.23	[85]
Effort (Effort)				
1. I find it difficult to behave in an energy conscious manner.	5	2.37	1.00	[87]
2. It takes up too much of my time to behave in an energy conscious manner.	5	2.27	1.05	[87]
Comfort attitude (ComfAtt)				
1. I am willing to sacrifice some comfort to behave in an energy conscious manner.	5	3.59	1.06	[88]
2. My quality of life will decrease when I behave in an energy conscious manner.	5	2.61	1.10	[87]
Personal norms (PerNorms)				
1. I feel guilty when I don't behave in an energy conscious manner.	5	3.30	1.14	[87]
2. I feel good about myself when I behave in an energy conscious manner.	5	4.00	0.94	[87]
Justification behaviour (Justification)				
1. There are more important things in life than protecting the environment, so not behaving in an energy conscious manner is to some extent justified.	6	2.57	1.43	[85]
2. The effects of one person's energy conscious behaviour are small, so it is not worth limiting yourself for the environment.	6	2.41	1.38	[85]
3. I am very environmentally friendly in most areas of life, so it's okay too, if I do not behave in an energy conscious manner.	6	3.04	1.45	[85]

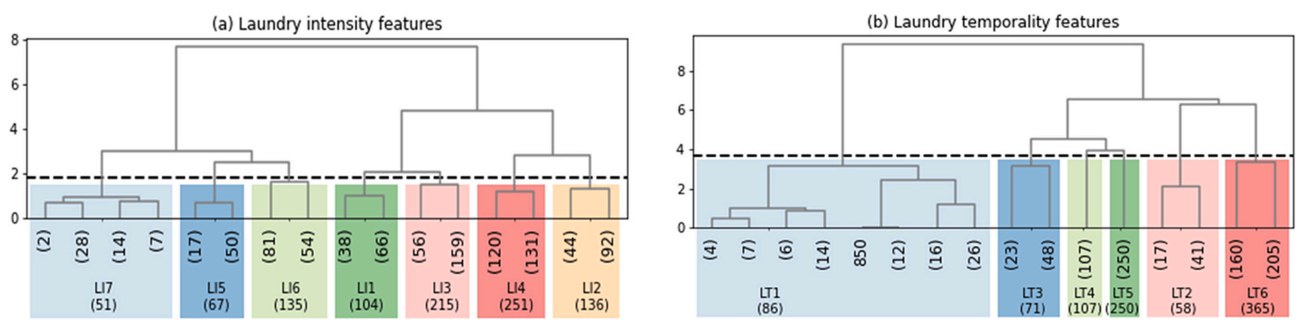

Fig. 6. Dendrograms hierarchical clustering of laundry intensity and temporality features.

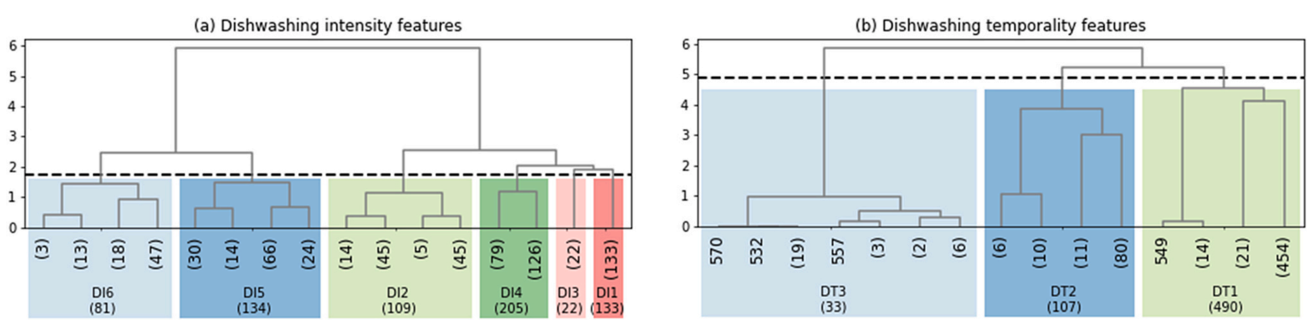

Fig. 7. Dendrograms hierarchical clustering of dishwashing intensity and temporality features.

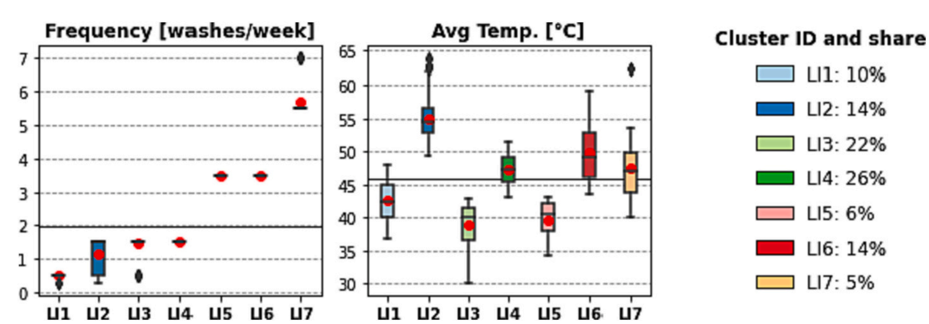

Fig. 8. Boxplots of laundry intensity patterns. Variable mean values for the whole sample (_) and individual clusters (●).

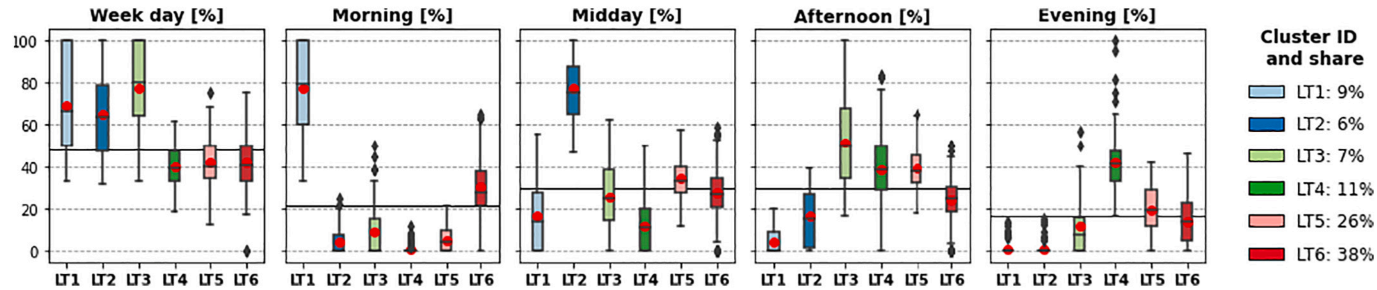

Fig. 9. Boxplots of laundry temporality patterns. Variable mean values are reported as (_) for the whole sample and (●) for individual clusters.

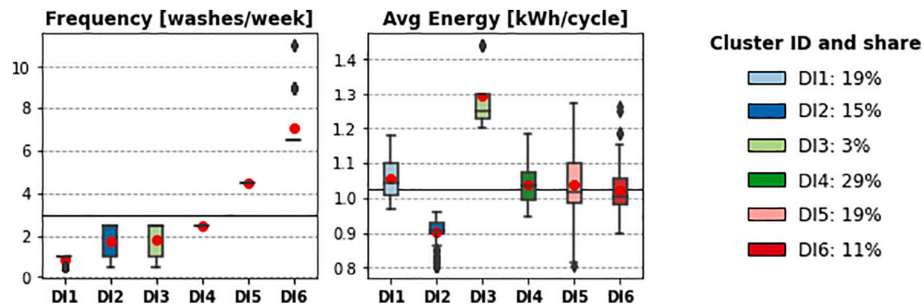

Fig. 10. Boxplots and scatterplot of dishwashing intensity patterns. Variable mean values for the whole sample (_) and individual clusters (●).

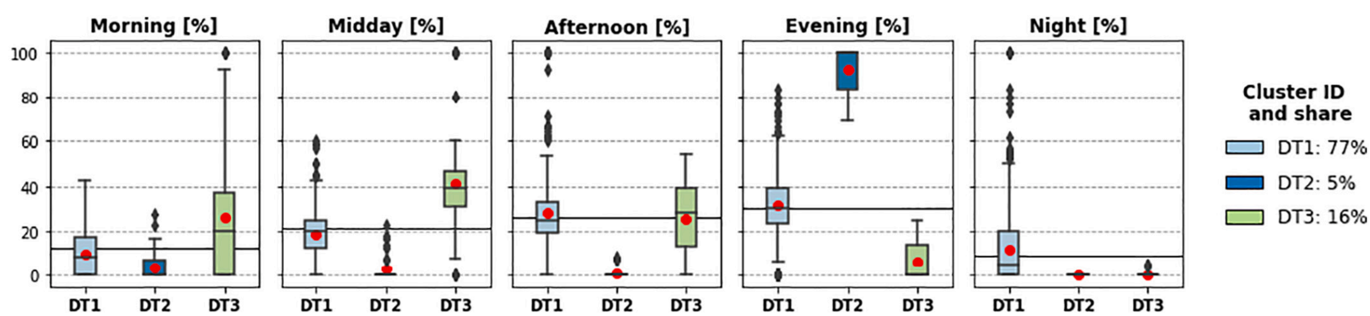

Fig. 11. Boxplots of dishwashing temporality patterns. Variable mean values are reported as (_) for the whole sample and (●) for individual clusters.

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