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Who is self-committed to climate action? Exploring decarbonisation actions and target gaps using carbon footprint calculator data in Japan

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ABSTRACT

Given the urgent need to promote climate-friendly behaviours, the implementation of carbon footprint calculators with actionable recommendations is increasing. This study analysed data from >7000 users of a Japanese carbon footprint calculator to investigate the characteristics and factors affecting voluntary commitment to decarbonisation actions and the gaps in achieving the 1.5-degree mitigation target. The results showed voluntarily committed actions were insufficient to meet the 2030 personal carbon footprint target, with only 31 %, 18 %, and 7.3 % of users potentially achieving targets in the domains of housing, mobility, and goods/services, respectively. The seven user segments that were identified exhibited very different levels of engagement. For example, 'lifestyle change enthusiasts' committed to as many as 25 actions, corresponding to an equivalent of 2.8 tCO$_2$e of footprint reduction, while 'curious bystanders' rarely committed to any actions. Demographically, younger and male users tended to prioritise high-impact actions, whereas female users and users aged 50–60 years old were more likely to commit to a range of actions. Notably, actions requiring substantial financial investment had an 8 % lower commitment probability, and 'shift' actions were 6 % less preferred than 'avoid' actions". These findings contribute to a deeper understanding of the considerable gap between self-committed actions and mitigation targets, and suggest that more effective use of footprint information could facilitate greater engagement. Tailored strategies could better motivate the 'curious bystanders' segment and encourage female and older users to focus on high-impact actions.

1. Introduction

Given the increasing urgency to rapidly decarbonise society, consumer behaviours contribute considerably to emissions throughout the lifecycle of products and services. Consequently, transitioning current lifestyles is crucial for achieving climate mitigation goals [1]. This is particularly true for affluent households, where overconsumption is an important driver of the environmental crisis [2]. Due to the substantial emissions gap that exists among personal carbon footprints, there is an increasing need for populations in affluent countries to rapidly reduce their carbon footprints by >60–80 % by 2030, and by 80–90 % by 2050 [3]. A variety of mitigation opportunities exist within the life cycles of products and services for meeting human needs and wants, such as mobility, housing, food, and goods [4]. However, previous studies have shown that individuals often lack a comprehensive understanding of the climate impacts induced by their own consumption, while overestimating the mitigation effects of their actions [5–7]. Personal carbon footprints can provide valuable information to consumers regarding their emission responsibilities, but an intuitive tool is needed to help consumers understand the problems and identify possible actions [8].

Carbon footprint calculators are designed to estimate an individual's personal carbon footprint and provide tailored feedback on their performance, along with suggestions for improvement [9]. By quantifying emissions through the life cycles of products and services consumed by households, carbon footprint calculators consider not only Scope 1 (direct emissions) and Scope 2 emissions (indirect emissions from electricity consumption), but also Scope 3 emissions (indirect emissions from other products and services) [10]. While previous research on these calculators has focused primarily on refining the methodologies used for footprint estimation [11–13], recent footprint calculators and related studies emphasise additional functionalities to facilitate behaviour change, such as personalised action recommendations (tips) and commitments (pledges) [14–16]. Action recommendations provide users with a list of potential behaviours to reduce their footprints, sometimes in conjunction with quantitative information on the footprint reduction potential of each action [17]. Commitments involve selecting actions that individuals are willing to take, either in the form of self-commitment (i.e. privately) or as a public commitment (i.e. declared to others), and which have been shown to increase effectively the adoption of mitigation actions [18–20]. The combination of commitments, action recommendations, and footprint calculations is expected to help consumers to better understand the current status of the impact that their own consumption is having on the climate. In addition, these activities also help to identify gaps relative to sustainable levels and facilitate the adoption of effective mitigation actions.

While the implementation of carbon footprint calculators with actionable recommendations is increasing, previous studies have not thoroughly examined the types of actions that have been self-committed using footprint calculators, or the gaps in achieving decarbonisation targets. The findings of an interview-based calculator study in Europe concluded that presenting individuals with reduction targets can encourage citizens to select more actions, although they only selected approximately half of the footprint reduction measures required to meet the 1.5-degree target [21]. User data from a Swedish calculator showed that one-third of users voluntarily set reduction targets, but actual footprints were reduced by only approximately 10 % [22]. Other studies investigated the types of actions selected by users [23–26]; however, these studies mostly considered a small number of participants or the application of multivariate statistical methods was limited.

Another important area that has not been addressed by existing research on carbon footprint calculators is heterogeneous user segments. Specifically, several studies on personal carbon footprints concluded that considerable heterogeneity exists among consumer segments [27,28]. Green marketing literature emphasises the need for consumer segmentation and positioning strategies [29,30], while targeting specific populations has also been considered an important element in public policy and political science [31,32]. Although such user segmentation provides valuable insights for promoting behavioural change towards decarbonisation, to the best of the authors' knowledge, no studies on carbon footprint calculators have focused on user segmentation and considered heterogeneity in their analyses.

In this study, we sought to investigate the types of actions that are self-committed using carbon footprint calculators and the extent of the resulting gaps relative to the mitigation target, considering heterogeneous user segments. For this purpose, we employed a binomial logit model to statistically analyse the types of actions committed by calculator users, using data collected from self-selected Japanese users of the carbon footprint calculator. Furthermore, the characteristics of users who actively made commitments were analysed in terms of user demography by Poisson regression and user segments by a latent class model. Finally, the gap between committed actions and the personal footprint target, as derived from the climate goals of the Paris Agreement, was examined with consideration of the different user segments.

2. Literature review

2.1. Characteristics of decarbonisation actions which are chosen by consumers

To address the substantial gaps in personal carbon footprints, effective decarbonisation actions need to be mainstreamed among the population; however, preferences for different types of actions vary. Several typologies of decarbonisation actions are related to household consumption. The Avoid-Shift-Improve (ASI) framework categorises mitigation measures into three types: reducing needs ('avoid'), shifting modes of consumption ('shift'), and improving product efficiency ('improve') [33]. 'Avoid' actions are sometimes referred to as curtailment behaviours (e.g. efforts to reduce consumption), whereas 'improve' actions are referred to as efficiency behaviours (e.g. one-time adoption of efficient technologies) [34].

Some 'improve' (efficiency) actions require substantial financial investment and longer planning times, which can pose significant barriers to adoption. These barriers may need to be addressed through structural strategies, such as changes in pricing, regulations, and physical and technical systems [35,36]. In contrast, some 'avoid' (curtailment) actions are relatively convenient and low-cost, making them easier to promote through information strategies, such as public campaigns [35]. Nevertheless, some 'avoid' and 'shift' actions may necessitate substantial lifestyle changes, which require support from infrastructure, cultural and social norms, and institutional systems [26,37]. Another important distinction is between high- and low-impact behaviours in terms of their objective environmental impacts; high-impact behaviours are typically more influenced by contextual factors rather than psychological factors, and are more difficult to change [26,35].

A few studies using footprint calculators have investigated which actions are preferred by consumers. Two studies from Europe and Japan concluded that actions related to food and goods were most frequently chosen [21,24]. Other studies from Europe reported that actions related to housing and food were the most preferred, with >20 % of calculator users reporting changes in these domains [38]. Another multi-country study in Europe also found that citizens preferred actions requiring financial costs ('improve' actions) over those involving substantial lifestyle changes [26]. In terms of mitigation potentials, two European studies concluded that the greater the potential for mitigation, the less willing people are to implement actions, which is contrary to the expected benefits of footprint calculators in promoting effective actions [21,26]. However, these studies relied largely on a small number of participants or did not employ multivariate statistical methods to account for different user segments.

An important consideration in analysing the types of actions is the sufficiency to achieve climate targets. Several scenario analyses based on carbon footprints indicate the need for large-scale lifestyle changes and the adoption of actions with higher mitigation potential [1,3,39,40]. However, these analyses often rely on exogenous assumptions about hypothetical changes in consumer behaviour, without accounting for individual preferences or abilities. Some exceptions include participatory approaches that use carbon footprint calculations to collaboratively identify scenarios or pathways for meeting climate goals. However, these studies typically employ more resource-intensive interventions, such as in-person workshops or interviews [21,24,26]. Despite the critical need to promote actions that align with climate targets, the mitigation potential of committed actions through online carbon footprint calculators, as well as the gaps between these actions and climate goals, remains largely unexplored.

2.2. Characteristics of consumers who actively engage in decarbonisation actions

Encouraging users to engage more actively with carbon footprint calculators is important, as many calculators struggle to attract and

retain users [15,22,38]. This is also important because preferences for types of decarbonisation actions and willingness to undertake these actions vary across different segments of the population. One line of research has focussed on psychological variables, such as attitudes and values, using consumer surveys [41,42]. From this perspective, several studies have investigated psychological determinants or outcomes of using footprint calculators by combining them with surveys [43–46].

Several studies not involving calculators have shown that demographic factors are associated with carbon footprints and climate-friendly behaviours. Some of these authors reported that female, younger or elderly, and metropolitan populations tend to have smaller personal carbon footprints [28]; however, current footprints may not fully account for additional mitigation actions. A meta-analysis on climate change beliefs showed that younger, female, more educated, and high-income individuals are more likely to believe in climate change, although this belief has limited explanatory power regarding willingness to take action [47]. A multinational regression study concluded that females tend to undertake more mitigation actions, while age exhibited an inverse-U-shaped relationship, with individuals aged 40–50 years old adopting the most actions [48]. However, a review study reported mixed findings on the influence of demographic factors on low-carbon actions, attributing the variability to cultural and regional differences and interactions with other factors [49]. Despite these findings from non-calculator studies, previous studies using carbon footprint calculators have not fully accounted for differences in user demographics in their analyses.

Another line of research focuses on unobserved factors to identify consumer segments based on choices, attitudes, and other attributes [50,51] or footprint data [27,28,52]. In relation to climate goals, our previous analyses found that none of the observed Japanese consumer segments currently live below the 1.5-degree target footprint for 2030 [28]. Segmentation is a valuable approach, particularly because demographic variables explain only a limited portion of consumer preferences and behaviours [30]. Therefore, applying segmentation analysis to user data from a footprint calculator can provide more nuanced user profiling and facilitate analysis of different user segments.

3. Methods

3.1. Overview of carbon footprint calculator with personalised action recommendations

This study uses user data from the Japanese carbon footprint calculator 'Jibungoto-planet', which was co-developed by some of the authors. 'Jibungoto' is a Japanese term that translates to "making it your own problem". The app was developed as open-source software through a participatory civic-tech approach, involving citizens, including software engineers, designers, and researchers, and was launched in August 2022 [67].

The calculator was designed to inform users about their personal carbon footprints and decarbonisation actions by providing personalised footprint reduction estimates and encouraging them to commit to specific actions (Fig. 1). After viewing narrative explanations about the importance of climate change, decarbonisation actions, and reduction targets for personal carbon footprints, users select one of four consumption domains: housing, mobility, food, and goods/services (Fig. 1 (a)). For their chosen domain, users answer seven to 10 questions about their consumption amount and intensity (using multiple choice and numerical answers) (Fig. 1(b)) and are encouraged to provide demographic information, including age, gender, and region. Subsequently, users are shown their estimated personal carbon footprints with a breakdown by subcategories (Fig. 1(c)). Here, a comparison with the country average is displayed using a percentage scale. Users are then presented with a personalised list of decarbonisation actions, ranked in descending order from high to low mitigation potential (Fig. 1(d)). The list is tailored to the user based on their estimated carbon footprints,

with non-relevant options (e.g. shifting to an electric vehicle for users that do not currently own a car) excluded. Users can select actions they wish to commit to and adjust their intended implementation rates across five levels (0 %, 25 %, 50 %, 75 %, and 100 %) for daily actions, or two levels (0 % or 100 %) for installing equipment (Fig. 1(d)).[1] Optionally, users can publicly commit to their selected actions by posting their list on social media platforms. Finally, users return to the domain summary, and can either select other domains for further estimation (Fig. 1(a)) or view a closing explanation designed to encourage more engaged actions in support of systemic changes.

The methodology and data used for estimating carbon footprints and personalised mitigation potentials from decarbonisation actions are based on the methodological framework and Japanese footprint data developed by some of the authors [39]. The questionnaire items in the calculator are linked to the carbon footprint database to estimate the user's footprint and the mitigation potential of relevant actions. The calculation methods and software are publicly available as open-source software in a GitHub repository [68]. Different types of the 34 decarbonisation actions included in the calculator are summarised in Table 1. More detailed descriptions of actions and methodological details of carbon footprint data cleaning are provided in Tables S1 and S2 in Supplementary Information 1 (SI 1).

3.2. User data collection and preparation

This study analysed user data collected by the Japanese carbon footprint calculator 'Jibungoto-planet' for the period from its launch on 31 August 2022 to 29 March 2024. Since its launch, the calculator has been promoted to the Japanese public through newspapers, television, online articles, and social media. Since the use of the calculator is voluntary, the users are a self-selected, pro-environmental sub-population motivated to consider or act on climate change issues. The data collected include demographic information (age group, gender, and region), responses to the footprint estimation questionnaire (consumption amount and intensity), the results of self-commitments[2] to decarbonisation actions (dichotomous choice: 'yes' or 'no'; intended implementation rates ranging over 0–100 % for 34 actions). The total number of users, regardless of the availability of demographic variables, was 34,276; however, this original dataset contained a large number of early dropouts and low-quality responses. To ensure data quality and enable cross-analysis with valid demographic variables, this study used only data with valid demographic responses. Although all users agreed to the terms of service before using the calculator, the research plan for this specific study was posted on the website, allowing users to opt out. Since obtaining informed consent from users requiring parental authorization was not possible, data furnished by users younger than 20 years old were excluded, resulting in a final valid sample size of 7188. More details of data preparation and cleaning are provided in SI 1. The use of data in this study was approved by the institutional review board (IRB) of the National Institute for Environmental Studies (No.: 2023-007).

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[1] Implementation rate refers to the extent of change from the current consumption patterns to the ideal full adoption of decarbonisation actions. For example, for those currently using public transport only once a week, increasing the use of public transport for commuting to every working day (5 days) represents 100 % implementation, while increasing that to 3 days per week represents 50 % implementation. For more details, please refer to the original papers [39].

[2] Although the calculator includes a public commitment function (posting a list of selected actions on a social network), the use of social networks is not tracked and is not available as part of user data. Therefore, this study focuses solely on self-commitment. It should be noted that some of the self-committed users may also have publicly committed to actions.
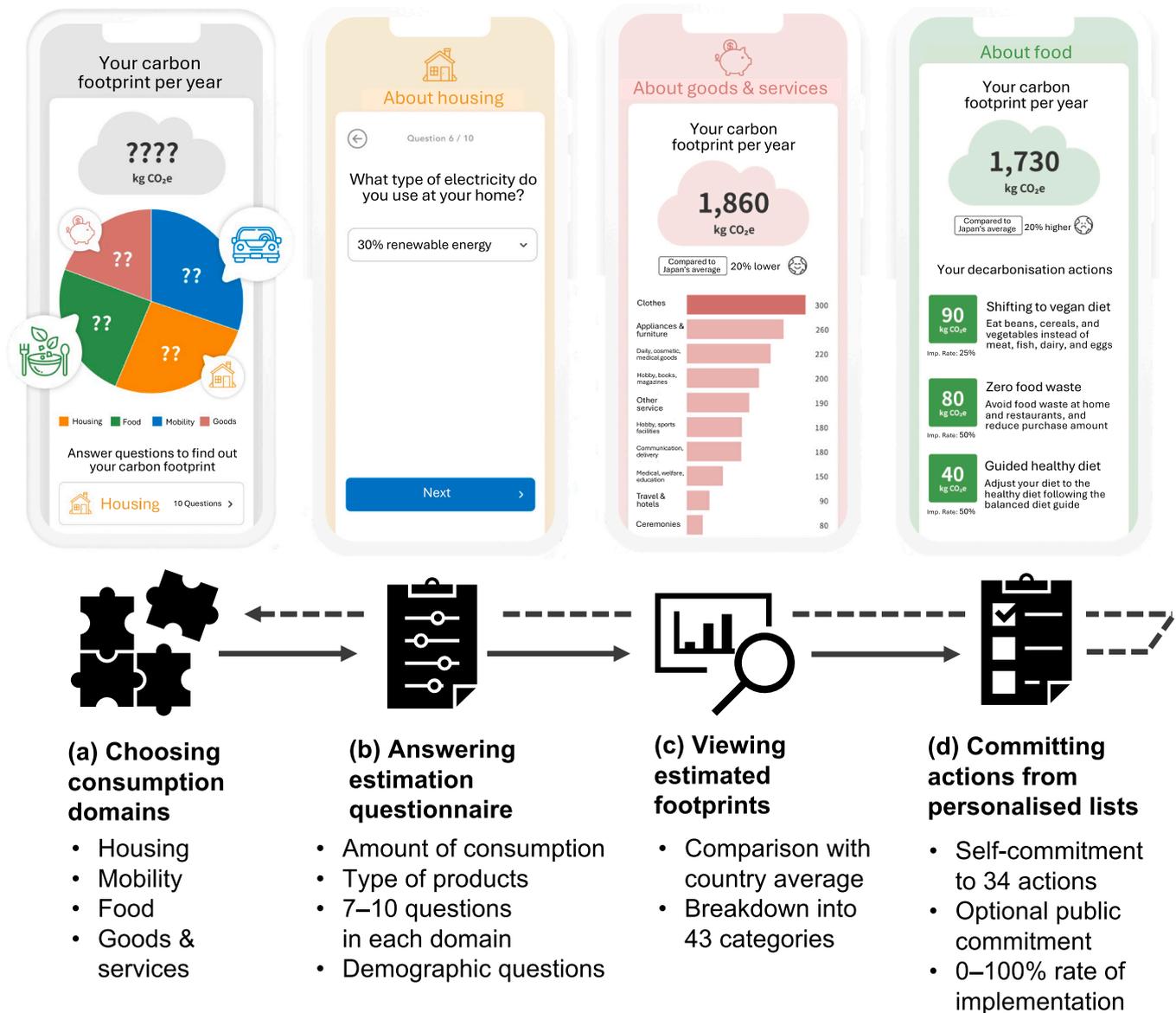
Fig. 1. Overview of the carbon footprint calculator with personalised action recommendations. The user interface shown above has been translated into English.

Table 1
Number of decarbonisation actions included in the carbon footprint calculator.

	Type			Investment		Total
	Avoid	Shift	Improve	Yes	No	
Housing	5	2	3	4	6	10
Mobility	4	4	2	2	8	10
Food	1	5	2	0	8	8
Goods/services	4	1	1	0	6	6

Cross-tabulation of the number of decarbonisation actions by type (avoid, shift, or improve), necessity of investment (yes or no), and consumption domain (housing, mobility, food, or goods/services). More detailed descriptions of actions are included in Tables S1 and S2 in SI 1.

3.3. Descriptive and statistical analysis

First, descriptive statistics on the completion/dropout rates for estimating carbon footprints and committing to decarbonisation actions in each consumption domain were calculated and visualised as a bar chart. To understand the characteristics of users who actively commit to actions, the number of actions committed to per consumption domain was regressed on demographic variables (age group, gender, and region), consumption domain (housing, mobility, food, and goods/services), and interaction terms between demographic variables and domains. A zero-inflated Poisson regression model was used because the data contained an excess of zeros (i.e. a substantial number of users did not commit to any actions within a domain). To identify common characteristics across domains, the model was estimated using pooled data for 7188 users × 4 domains (N = 28,752), with the type of domain included as an explanatory variable. Random intercepts for user identifiers were incorporated to account for repeated measurements, as each user contributed to four domains. To interpret the results, the predicted number of committed actions was quantified based on combinations of the explanatory variables.

The second analysis employed a latent class model to identify unobserved characteristics of users beyond the observed demographic variables. The outcome variables comprised commitments to 34 types of decarbonisation actions, while demographic factors (age group, gender, and region) were included as covariables of the latent class. To focus on user segmentation, the model was estimated using cross-sectional data for 6977 users (N = 6977) who completed carbon footprint estimation in at least one domain. The estimation process involved testing a preset

number of classes, ranging from 2 to 15, with 10 repeated iterations for each class number, and the minimum class size was set at 1 % of the total users. The final number of classes was determined by the Bayesian Information Criterion (BIC) as the model comparison indicator, and the classes were manually labelled. The profiling of classes was carried out by summarising the commitment probability to the 34 decarbonisation actions and demographic characteristics of each class. Differences between classes were statistically tested using Pearson's Chi-squared test for numerical variables and the Kruskal-Wallis rank sum test or Fisher's exact test for categorical variables.

To further investigate the characteristics of decarbonisation actions committed to by more users, binomial logit regression analysis was conducted using data on commitments to 34 types of decarbonisation actions. The explanatory variables included the type of mitigation actions (categorical: avoid, shift, and improve), the necessity of investment (dichotomous: yes (1) or no (0)), the consumption domain (categorical: housing, mobility, food, and goods/services), and the mean footprint reduction potential (numerical: tCO_2e/cap/year), along with interaction terms with user demographic variables. To focus on different decarbonisation actions rather than individual users, the model was estimated using pooled data from 6977 users × 34 actions (N = 237,218). Similar to the previous analysis, random intercepts of user identifiers were included to account for repeated measurements, as each user contributed 34 actions. To interpret the results, the predicted commitment probability for each action was analysed in relation to combinations of the explanatory variables.

The final analysis aimed to investigate the gap between committed and recommended decarbonisation actions and the decarbonisation targets. For this purpose, the estimated carbon footprint reductions from committed actions (i.e. those chosen by users) and recommended actions (i.e. those recommended to users) were compared against the decarbonisation targets. The gap between the remaining carbon footprints, assuming full implementation of either the committed or recommended actions, was illustrated using area charts, with personal carbon footprint targets for 2030 and 2050 derived from the climate goals set out in the Paris Agreement [3,28].

4. Results

4.1. Overview of users and calculator use

The summary statistics of the demographic variables of the calculator users are included in Table S3 in SI 1. There were slightly more male users (55 %) than female users (45 %), with a higher proportion of users in their 20s (22 %) and a lower proportion in their 60s (14 %) and 70s (8 %) compared to the national population. In terms of region, more users were from the Kanto area, which includes the Tokyo metropolitan area (53 %), while other provincial regions had somewhat fewer users. Although there was a slight bias towards younger and metropolitan users, the demographic distribution of user data was broadly similar to that of the national population.

The proportion of users who completed or dropped out of footprint estimation and commitment to actions is shown in Fig. S1 in SI 1. On average, users completed footprint estimation in 2.5 consumption domains and self-committed to at least one action in 1.7 domains. Among the four domains, housing was the most frequently completed (86 % completed footprint estimation, and 51 % made at least one commitment), followed by food (62 % and 45 %), mobility (52 % and 39 %), and goods and services (47 % and 35 %). Among the valid users analysed in this study, the drop-out rate during footprint estimation was relatively low, with only 5–11 % dropping out after starting the footprint estimation for each domain. However, a substantial number of users dropped out when choosing decarbonisation actions; among users who completed footprint estimation, 43 % (for housing) to 27–30 % (for other domains) of users did not commit to any actions. This large difference in dropout rates between estimation and commitment suggests

that the willingness to take action is significantly lower than the interest in understanding personal carbon footprints.

4.2. Characteristics of users who actively commit decarbonisation actions

To understand the characteristics of users who actively commit decarbonisation actions, the number of committed actions was regressed on user demographics using a zero-inflated Poisson regression model. While the estimated coefficients are presented in Table S4 in SI 1, the predicted numbers of committed actions by domain and demographic factors are illustrated in Fig. 2 (for each variable) and Fig. S2 in SI 1 (by domain with cross-analysis by demographics) to provide more intuitive results. Overall, users tend to commit to more actions related to food (2.6 actions among those who committed to at least one action without considering zero-inflation, and 1.2 actions among all users, considering zero-inflation), followed by goods/services (2.0 and 0.8 actions), housing (1.7 and 1.0 actions), and mobility (1.7 and 0.7 actions). This order of preferred commitment domains contrasts with footprint estimation, where the most and least frequently used domains were housing and goods/services, respectively.

The tendency to commit to actions differed by user demographics. Overall, females tended to commit to more actions (2.2 and 1.0 actions) than males (1.9 and 0.9 actions) (Fig. 2). However, this gender difference was only observed for food (2.9 actions by females compared to 2.3 actions by males among those who committed to at least one action, without considering zero-inflation) and goods/services (2.3 compared to 1.8 actions) (Fig. S2 in SI 1). Regarding age, among those who committed to at least one action, older users tended to commit to more actions (2.5 actions by users in their 70s compared to 1.6 actions by users in their 20s). However, this tendency becomes less apparent when considering users who never commit to any actions; in particular, users in their 70s are more likely not to choose any actions, resulting in a peak in commitment among users in their 50s and 60s (Fig. 2). This age-related difference was generally observed across consumption domains, with the exception of housing, where users in their 70s showed the highest number of commitments (Fig. S2). Regional differences were not very pronounced. Users in the regions with three large metropolitan areas (Kanto, Kinki, and Tokai) and regions with extreme weather (Hokkaido in the north and Kyushu/Okinawa in the south) tended to commit to slightly more actions compared to other regions, but this tendency was only observed among those who committed to at least one action (Fig. S2).

4.3. Segmentation of users by the types of committed decarbonisation actions

To identify unobserved characteristics of users beyond demographic factors, a latent class model was employed. The optimal number of latent classes was determined to be seven, based on the BIC (Table S5 in SI 1). These latent classes represent unobserved factors influencing users' self-commitment to the 34 decarbonisation actions, with each user probabilistically assigned to one of these latent classes. Consequently, calculator users were segmented into seven groups, with their commitment probabilities to decarbonisation actions and segment sizes illustrated in Fig. 3. The demographic profile, number of committed actions, and mitigation estimates for each identified user segment are summarised in Table 2.

The analysis revealed considerable variation on the tendency to commit to different types of actions among user segments. Statistical tests of segment differences also confirmed that the segments differed significantly in terms of demographics and committed actions (*p* < 0.001). The most enthusiastic segment towards decarbonisation was identified as '*lifestyle change enthusiasts*'. Although this segment comprised only a small proportion of users (1.6 %), they committed to an average of 25 across the four domains, resulting in a total committed carbon footprint reduction of approximately 2.8 tCO_2e/cap/year
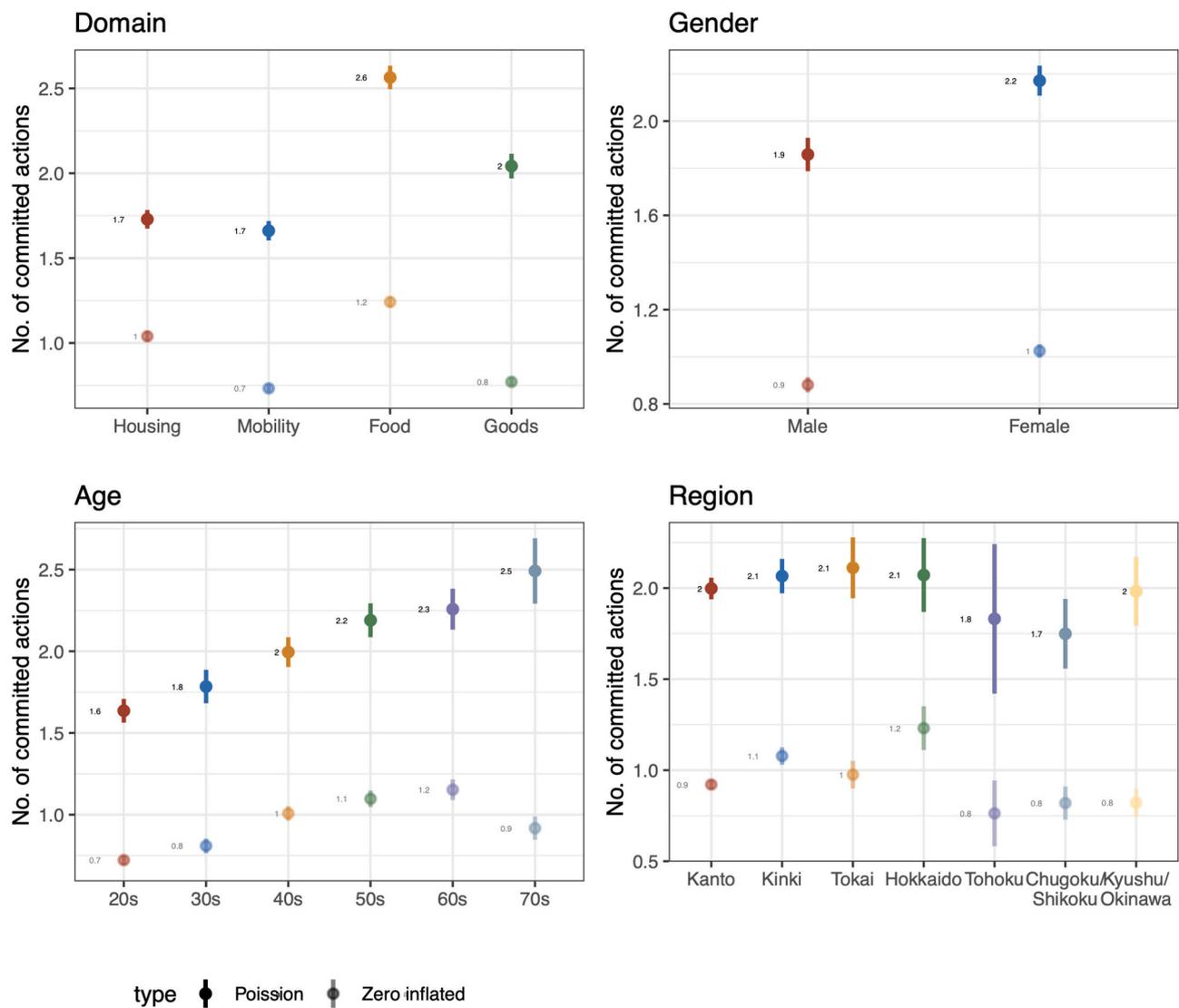
Fig. 2. Predicted number of committed actions by consumption domain or demographic variables (zero-inflated Poisson model). Points and bars represent the predicted mean and 95 % confidence intervals, respectively. Thick and thin coloured lines indicate Poisson counts without zero inflation (predicted number of committed actions among those who committed to at least one action) and with zero inflation (predicted number of committed actions among all users), respectively. Non-focal predictors (variables not shown in each panel) are marginalised over the observations in the data. The model was estimated using pooled data from 7188 users × 4 domains (N = 28,752).

(Table 2). This segment commits to actions from all four domains and is even inclined to select actions that are less popular among other segments, such as installing solar panels or heat pumps for hot water supply, ridesharing and carsharing, and adopting vegan or vegetarian diets (Fig. 3). This segment tends to include a slightly higher proportion of males (60 %) and elderly users (32 % are in their 60s and 70s).

The second most enthusiastic segment comprised the '*dematerialisation enthusiasts*', which is a segment that represented a small but substantial number of users (11 %). On average, this segment committed to a total of 13 actions (1 tCO$_2$e/cap/year of committed reduction), but mostly their focus was primarily on the food and goods/services domains. They are proactive in minimising excessive use and waste of clothing, hobby goods, consumables, electronics, and food. Additionally, they are keen on shifting their diet towards guided, healthy, and environmentally friendly meals, incorporating seasonal and local food ingredients. Another small but notable segment (4 % of users) consisted of the '*sustainable diet enthusiasts*'. This segment committed to an average of 5.4 actions related to food, including reducing food waste, shifting to guided meals, and reducing red meat consumption, with a commitment probability of 70 % or higher. However, vegan and vegetarian diets

remained unpopular even within this segment, with a commitment probability of <30 %. The total committed footprint reduction only reached about 0.7 tCO$_2$e/cap/year. These latter two segments are more likely to be female (61–63 %) and middle-aged (27–30 % are in their 50s) users.

The remaining majority of users (23 %) consists of '*hesitating beginners*', who are more likely to include younger users (24 % are in their 20s). This segment tends to commit different domains but, on average, only chooses only 1.1–1.6 actions per domain. This segment generally selected more popular actions and rarely committed to less popular actions, such as improving insulation, living in compact houses, installing solar panels, or adopting carsharing or ridesharing and vegetarian or vegan diets. Another interesting segment consisted of the '*effective environmentalists*' (8 %), who are more likely to be male (76 %), younger (37 % are in their 20s), and from metropolitan areas (63 % from the Kanto region). Although the number of committed actions was not particularly high for '*effective environmentalists*' (only 4.1 actions across the four domains), they tended to select the most effective actions for carbon footprint reduction, such as adopting zero-energy housing, using electric vehicles charged by renewable energy, shifting to vegan and
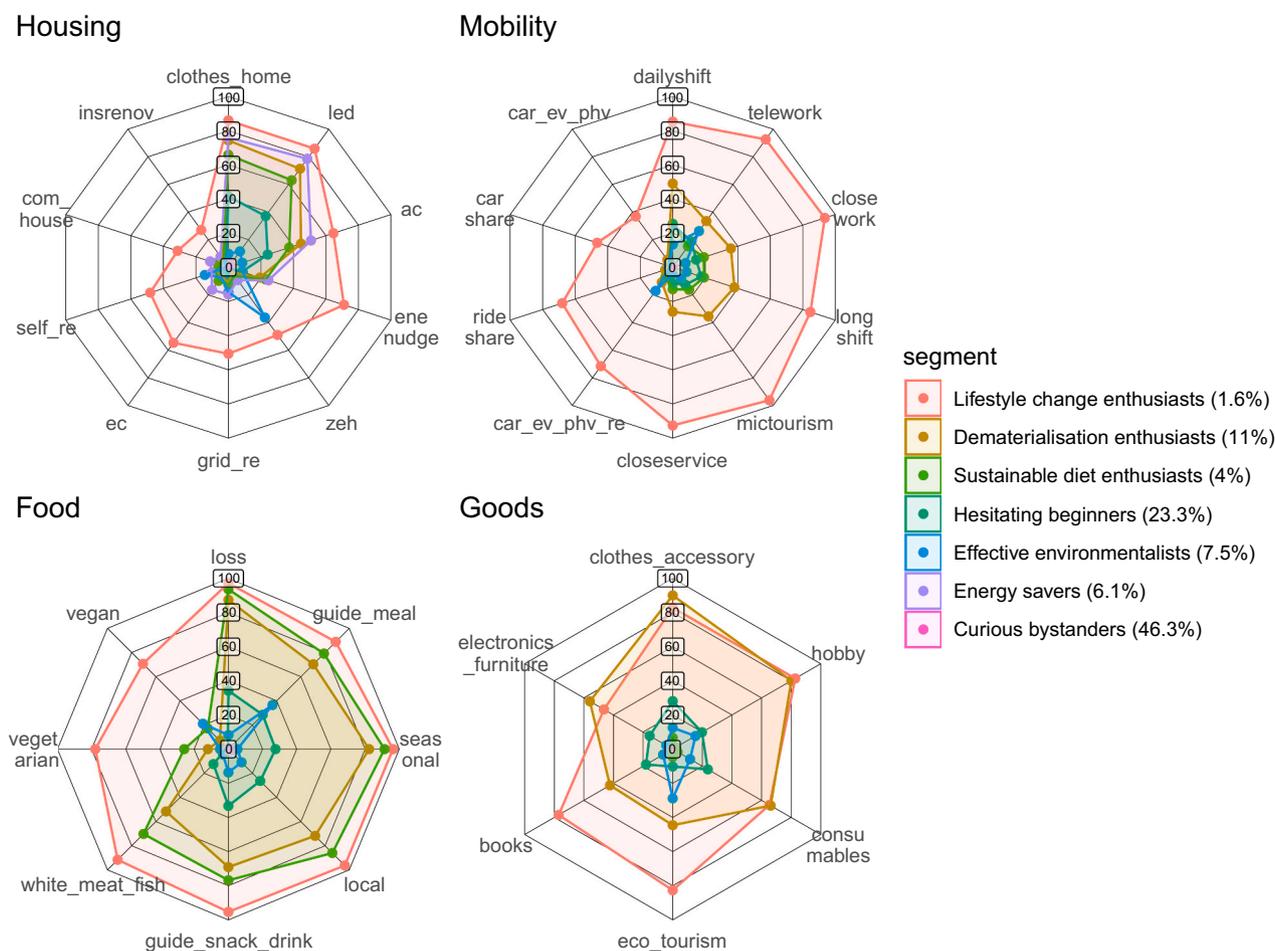
Fig. 3. Mean commitment probability of decarbonisation actions by user segments (latent class model). Colours indicate user segments (latent class), and the percentage in parenthesis in the legend represent the size of each user segment. The radius of the radar chart (numbers range from 0 to 100) reflects the commitment probability for each user segment in percent. The model was estimated using cross-sectional data from 6977 users (N = 6977). For definitions of the abbreviations given in the graphs, please refer to Table S1 in the SI.

guided meals, and engaging in eco-tourism. As a result, their total committed footprint reduction was relatively high, at about 1.4 tCO₂e, compared to the number of actions committed. Another notable segment was '*energy savers*' (6 %), who are more likely to commit to relatively easy and popular actions related to housing, such as wearing warm clothes and switching to LED lighting, but rarely committed to actions in other domains. Lastly, the largest segment, comprising as much as 46 % of users, was the '*curious bystanders*', who almost never committed to decarbonisation actions despite estimating their carbon footprints.

4.4. Characteristics of decarbonisation actions often committed by calculator users

To understand the characteristics of actions often committed by users, the commitment probability for 34 actions was analysed using a binomial logit model. While the estimated coefficients are provided in Table S7 in SI 1, the predicted commitment probabilities by action characteristics are illustrated in Fig. 4 (by each variable) and Figs. S3 and S4 (cross-analysis with age, gender, and region) in SI 1 for more intuitive results. The analysis revealed clear differences in the types of actions: 'avoid' actions had the highest commitment probability (15 %), followed by 'improve' actions (12 %), while 'shift' actions had the lowest commitment probability (8.4 %) (Fig. 4). The unpopularity of 'shift' actions did not vary by gender; the higher commitment probabilities observed for females in 'avoid' and 'improve' actions did not apply to 'shift' actions (Fig. S3 in SI 1). Moreover, actions requiring

substantial financial investment had significantly lower commitment rates (4.8 %) compared to other actions (13 %) (Fig. 4). This trend showed a distinct relationship with gender and age. Males were slightly more likely to commit to investment actions than females, while the opposite was true for non-investment actions. In addition, higher commitment rates by middle-aged users (40s–60s) were particularly apparent for non-investment actions (Fig. S3 in SI 1). These findings reconfirm the challenges encountered in adopting decarbonisation actions that require financial investment and substantial lifestyle changes.

In terms of carbon footprint reduction potentials, there was a slight trend indicating that higher footprint reduction was associated with a greater commitment probability, after controlling for other variables; e. g. actions with a 1.5 tCO₂e reduction potential had a 0.5 % higher probability of being committed to compared to those with a 0.5 tCO₂e potential (Fig. 4). However, this influence varied by demographic group. Thus, young to early-middle-aged males (20s–40s) and young females (20s) were more likely to commit to actions with higher footprint reduction potentials. Conversely, females in their 50s to 70s and males 70 years old and above tended to show a decreasing likelihood of committing to actions as the footprint reduction potential increased. These results suggest that, on average, calculator users are more likely to commit to higher-impact actions after controlling for factors such as domain, action type, and investment requirement. However, this tendency varies and depends on demographic group and user segment.

Table 2
Profiles of the identified user segments (latent class model).

	Overall N = 6977[1]	Lifestyle change enthusiasts N = 115[1]	Dematerialisation enthusiasts N = 771[1]	Sustainable diet enthusiasts N = 282[1]	Hesitating beginners N = 1624[1]	Effective environmentalists N = 525[1]	Energy savers N = 428[1]	Curious bystanders N = 3,232[1]	p-Value[2]
Gender									<0.001
Male	3786 (54 %)	69 (60 %)	300 (39 %)	104 (37 %)	897 (55 %)	398 (76 %)	211 (49 %)	1807 (56 %)	
Female	3191 (46 %)	46 (40 %)	471 (61 %)	178 (63 %)	727 (45 %)	127 (24 %)	217 (51 %)	1425 (44 %)	
Age									<0.001
20s	1483 (21 %)	15 (13 %)	80 (10 %)	41 (15 %)	386 (24 %)	192 (37 %)	32 (7.5 %)	737 (23 %)	
30s	1101 (16 %)	11 (9.6 %)	89 (12 %)	38 (13 %)	283 (17 %)	82 (16 %)	64 (15 %)	534 (17 %)	
40s	1391 (20 %)	25 (22 %)	180 (23 %)	57 (20 %)	334 (21 %)	94 (18 %)	88 (21 %)	613 (19 %)	
50s	1456 (21 %)	27 (23 %)	206 (27 %)	86 (30 %)	326 (20 %)	77 (15 %)	94 (22 %)	640 (20 %)	
60s	987 (14 %)	23 (20 %)	155 (20 %)	40 (14 %)	210 (13 %)	55 (10 %)	74 (17 %)	430 (13 %)	
70s	559 (8.0 %)	14 (12 %)	61 (7.9 %)	20 (7.1 %)	85 (5.2 %)	25 (4.8 %)	76 (18 %)	278 (8.6 %)	
Region									<0.001
Kanto	3652 (52 %)	61 (53 %)	406 (53 %)	147 (52 %)	777 (48 %)	331 (63 %)	198 (46 %)	1732 (54 %)	
Kinki	1303 (19 %)	24 (21 %)	151 (20 %)	70 (25 %)	363 (22 %)	53 (10 %)	117 (27 %)	525 (16 %)	
Tokai	515 (7.4 %)	10 (8.7 %)	62 (8.0 %)	21 (7.4 %)	128 (7.9 %)	19 (3.6 %)	41 (9.6 %)	234 (7.2 %)	
Hokkaido	324 (4.6 %)	4 (3.5 %)	38 (4.9 %)	11 (3.9 %)	99 (6.1 %)	26 (5.0 %)	15 (3.5 %)	131 (4.1 %)	
Tohoku	415 (5.9 %)	6 (5.2 %)	31 (4.0 %)	6 (2.1 %)	105 (6.5 %)	32 (6.1 %)	16 (3.7 %)	219 (6.8 %)	
Chugoku/Shikoku	351 (5.0 %)	3 (2.6 %)	36 (4.7 %)	8 (2.8 %)	86 (5.3 %)	26 (5.0 %)	23 (5.4 %)	169 (5.2 %)	
Kyushu/Okinawa	417 (6.0 %)	7 (6.1 %)	47 (6.1 %)	19 (6.7 %)	66 (4.1 %)	38 (7.2 %)	18 (4.2 %)	222 (6.9 %)	
No. of committed actions									
Total	4.0 (5.3)	25.0 (4.1)	13.3 (3.0)	9.2 (2.9)	5.2 (2.1)	4.1 (2.1)	3.2 (1.6)	0.1 (0.3)	<0.001
Housing	1.1 (1.5)	5.7 (2.9)	2.5 (1.3)	2.4 (1.9)	1.3 (0.9)	1.2 (1.3)	3.2 (1.6)	0.1 (0.3)	<0.001
Mobility	0.8 (1.4)	7.8 (2.0)	2.4 (1.5)	1.2 (1.6)	1.1 (0.9)	1.0 (0.7)	0.0 (0.0)	0.0 (0.1)	<0.001
Food	1.3 (2.0)	7.2 (1.5)	4.6 (1.5)	5.4 (1.3)	1.6 (1.0)	1.1 (0.7)	0.0 (0.2)	0.0 (0.1)	<0.001
Goods	0.8 (1.5)	4.4 (2.0)	3.8 (1.2)	0.2 (0.4)	1.2 (1.1)	0.8 (0.7)	0.0 (0.0)	0.0 (0.0)	<0.001
Carbon footprint reduction potentials of committed actions									
Total	444.2 (1018.1)	2816.5 (1638.5)	1037.2 (986.7)	652.1 (812.0)	437.0 (617.6)	1416.0 (2292.8)	483.8 (951.6)	40.6 (292.6)	<0.001
Housing	213.5 (801.1)	984.2 (1069.6)	275.5 (518.5)	282.1 (557.8)	137.6 (380.1)	1020.1 (2231.1)	483.2 (951.7)	36.6 (287.2)	<0.001
Mobility	142.5 (426.3)	1211.4 (1047.6)	405.2 (657.8)	225.4 (524.9)	201.0 (446.2)	270.2 (490.6)	0.0 (0.0)	3.3 (57.9)	<0.001
Food	31.1 (68.7)	215.3 (178.8)	94.4 (70.9)	130.8 (161.9)	33.8 (37.2)	47.9 (66.3)	0.5 (5.3)	0.6 (6.1)	<0.001
Goods/services	57.1 (173.1)	405.6 (570.2)	262.2 (316.8)	13.8 (52.7)	64.6 (132.3)	77.8 (109.4)	0.0 (0.0)	0.0 (0.5)	<0.001

[1] n (%); Mean (SD). The model was estimated using cross-sectional data from 6977 users (N = 6977).
[2] Pearson's Chi-squared test; Kruskal-Wallis rank sum test; Fisher's exact test.

4.5. Gaps between committed actions and decarbonisation targets

This section expands the analysis to investigate the gaps between the committed actions and decarbonisation targets at both the overall user and segment levels. The estimated carbon footprints, remaining carbon footprints assuming implementation of committed or recommended actions, and the proportion of target-achieving users are shown in Table S8 (overall users) and Table S9 (by user segments) in SI 1. As shown in Fig. 5(a), there was a large gap between voluntarily committed actions using the footprint calculator and the sustainable level of personal carbon footprints. Across all users, 21 %, 15 %, and 5.8 % had carbon footprints below the 2030 target in the housing, mobility, and goods/services domains, respectively. Assuming full implementation of the voluntarily committed actions by 2030, only 31 %, 18 %, and 7.3 % of users would achieve the target in the housing, mobility, and goods/services domains, respectively, while the remaining users would continue to exceed the target. The most challenging consumption domain for achieving the target was food, where almost no users currently meet the 2030 target (< 0.1 %), and nearly none (only 0.2 %) would achieve the target after implementing the committed actions.

At the segment level, the most progressive group, the 'lifestyle change enthusiasts', showed promising results, especially in the housing and mobility domains; assuming full implementation of voluntarily committed actions by 2030, 75 %, and 51 % of users in this segment could achieve the target (Fig. 5(b)). However, the majority still exceed the targets in the food and goods/services domains, with only 1.8 % and
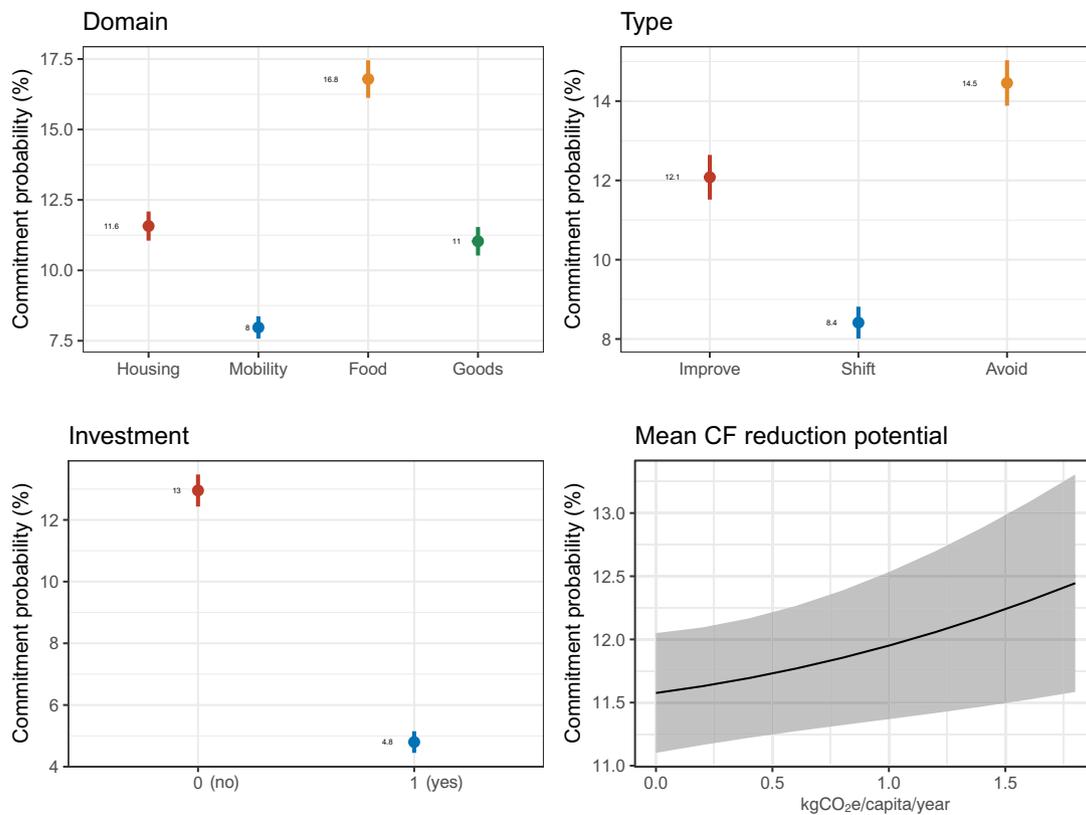
Fig. 4. Predicted probability of committing to actions by characteristics of actions (binomial logit model). Points and bars indicate the predicted mean and 95 % confidence intervals, respectively. Non-focal predictors (variables not shown in each panel) are marginalised over the observations in the data. The model was estimated using pooled data from 6977 users × 34 actions (N = 237,218). CF: carbon footprint.

13 % of users meeting the target, respectively. Another promising segment was '*effective environmentalists*', with 75 % of the users in this group potentially achieving the target in the housing domain; however, no similarly promising results were observed in any other domains (Fig. 5(c)). Results for other user segments are shown in Fig. S5 in SI 1. These segment-level results indicate that even among the most active segment in voluntary commitment to actions, the mitigation gap for personal carbon footprints remains very substantial, especially in domains other than housing.

5. Discussion

5.1. User engagement to carbon footprint calculators

The analyses revealed varying levels of engagement with carbon footprint calculators and self-commitments across different demographic groups and user segments. The results of the zero-inflated Poisson analysis indicated that female and middle-aged to early-elderly users tended to commit to the highest number of actions. These findings were broadly consistent with previous studies on willingness to adopt mitigation measures [48] and personal carbon footprints [28]. The latent class model further identified seven distinct user segments beyond demographic characteristics, including '*lifestyle change enthusiasts*', '*efficient environmentalists*', and '*curious bystanders*'. The identification of these user segments is a unique contribution of the present study, as no previous studies have investigated user segments of carbon footprint calculators. These identified demographic groups and user segments could inform targeted interventions, such as providing food- and goods-related footprint information to females, or for incentivising '*curious bystanders*' who completed footprint estimation to implement additional actions.

One of the key issues identified in the analysis was the gap between

footprint estimation and commitment to actions. On average, 27–43 % of users dropped out during the action selection phase, compared to only 5–11 % who dropped out during the footprint estimation process. The '*curious bystanders*' segment, consisting of users who almost never select any actions after footprint estimation, accounted for as much as 46 % of users. Therefore, ensuring that users who have completed footprint estimation proceed to understand the recommended actions and commit to them is a critical area for improving the effectiveness of carbon footprint calculators. In terms of consumption domains, users showed a greater interest in learning about their footprints in the housing, food, and mobility domains, but their commitment rates were higher for food and goods/services. These gaps are noteworthy because, to encourage people to calculate and learn about their footprints, focussing on consumption domains with a high share of Scope 1 and 2 emissions (direct emissions and indirect emissions from electricity), such as housing and mobility, could be an effective entry point. However, when encouraging action, domains related to Scope 3 emissions (indirect emissions through other products and services), such as food and goods/services, could be more effective. These differences suggest that there is a need for footprint-based interventions to address both direct and indirect emissions and for encouraging users to broaden their focus to include a wider range of household consumption domains.
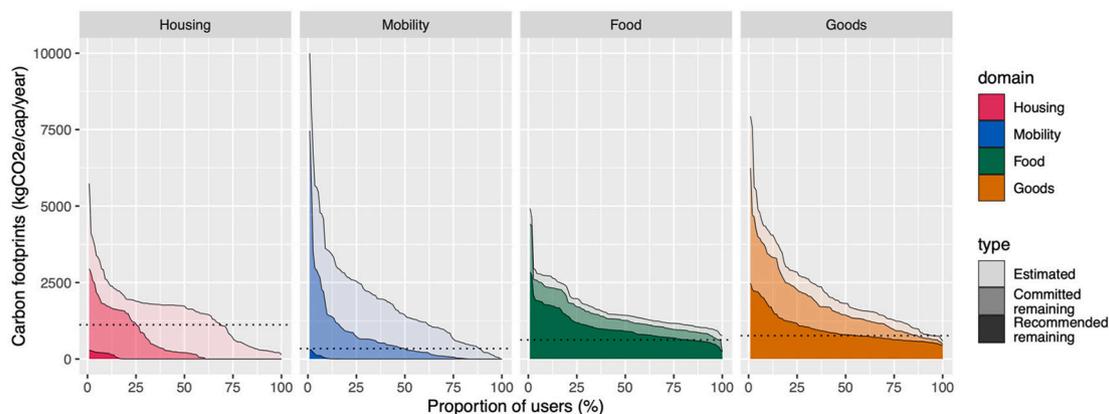
5.2. Types of decarbonisation actions committed to by calculator users

Our analyses identified the types of actions that calculator users are more or less likely to commit to. The most significant factor was the need for substantial financial investment, which resulted in an 8 % decrease in commitment probability. This finding appears to contradict those of a study that employed citizen thinking labs, which reported a preference for cost-involved actions [26]. However, this difference could be attributed to different definitions for 'investment'; in the present study,
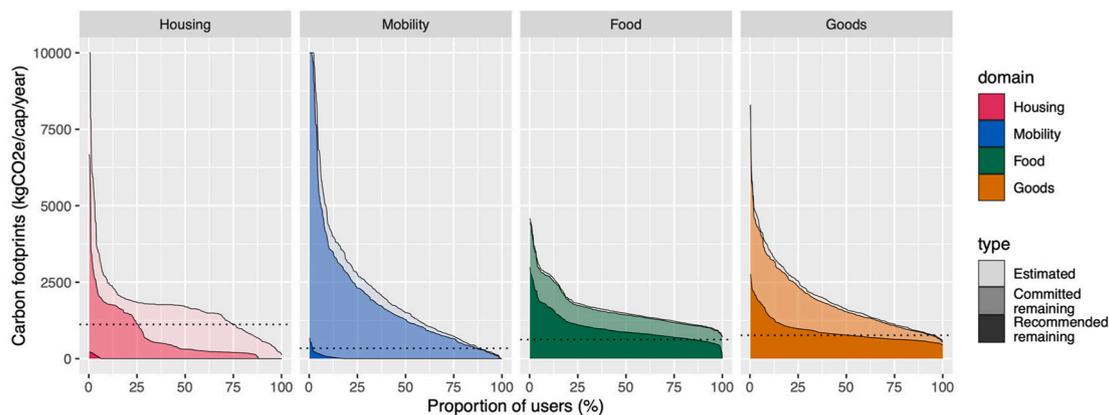
(a) Overall users
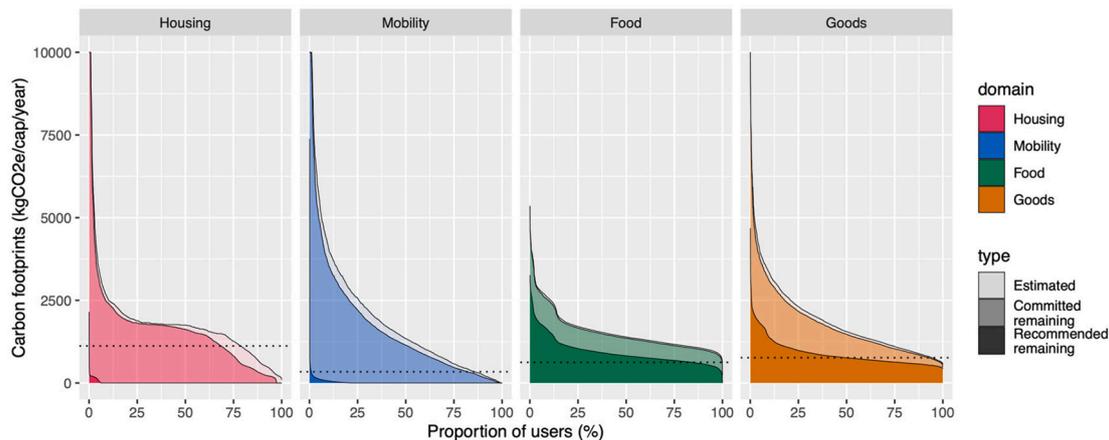
(b) 'Lifestyle change enthusiasts' segment

(c) 'Effective environmentalists' segment

Fig. 5. Distribution of estimated personal carbon footprints and remaining footprints assuming implementation of committed and potential decarbonisation actions. The height, width, and area of the graph represent the carbon footprint per capita, the proportion of users exceeding the carbon footprint, and the total carbon footprint, respectively. Lines above the thin-, medium-, and thick-coloured areas indicate the current personal carbon footprints, the remaining footprint assuming full implementation of committed actions, and the remaining footprint assuming full implementation of recommended actions, respectively. The dotted line represents the 2030 per capita personal carbon footprint targets, adapted from [3,28]. Carbon footprints in the graph were truncated at 10,000 kgCO₂e due to high skewness. The number of samples varies depending on the availability of domain-specific carbon footprint estimates: N = 6587 (housing), N = 3935 (mobility), N = 4702 (food), and N = 3602 (goods/services) for overall users in (a). The intersection points between the dotted and solid lines indicate the proportion of users who achieve, or do not achieve, the target based on their estimated or remaining carbon footprints. Results for other segments are shown in Fig. S5 in SI 1.

investment actions are defined as those requiring substantial financial investment (e.g. installing solar panels or purchasing electric vehicles), rather than including all 'improve' actions, as in the previous study. Furthermore, 'shift' actions were the least committed to by users, with a commitment rate of 6 % lower than the most committed 'avoid' actions. This finding is consistent with a previous calculator study that found modal choice to be the least preferred option [53]. However, differences in sampling methods might have influenced the types of actions users committed to, in addition to the above reasons. The user dataset in this study was relatively large (over 7000 users), but data were self-selected. In contrast, the previous studies mentioned above relied on recruitment surveys with demographic quotas, though their sample sizes were small (much fewer than two hundred participants) [26,53].

Another key consideration is that commitment to actions may depend not only on users' internal factors, such as preferences, but also on external factors, such as financial and physical constraints. In this context, the lower levels of voluntary commitments by calculator users can be explained by existing literature, which highlights the need for structural support, such as changes in pricing, regulations, and physical and institutional infrastructure, to enable actions that require financial investment and substantial lifestyle changes [35–37]. Such support could be tailored to user subgroups that exhibit stronger differences in action preferences, such as encouraging males to adopt investment actions or females to engage in food- and goods/service-related actions.

The results also showed a tendency for users to be more likely to commit to actions with a higher footprint reduction potential. This tendency was not observed across all users, but was specific to young-to-middle-aged males and young female users. The presence of the '*efficient environmentalist*' segment also confirms that some users are particularly interested in adopting actions with substantial footprint reduction impacts. This result is encouraging, as it suggests that the calculator could potentially promote commitments to impactful actions, at least for certain user segments. Although this result appears to contradict previous studies which concluded that people tend to select actions with lower mitigation potentials [21,26], the difference can be explained by methodological approaches. Our findings were derived using multivariate statistical methods, where the effects of mitigation potentials were assessed after controlling for other explanatory variables (such as distinctions among ASI categories, consumption domains, and financial investment). In contrast, the conclusions of the previous studies were based on descriptive analyses alone.

5.3. Gap analysis with the climate goal of the Paris Agreement

Our gap analysis revealed that the actions voluntarily committed to by users of the calculator were far from sufficient for meeting the 2030 personal carbon footprint targets. This gap is striking given that the calculator users are a self-selected group already engaged in climate issues. Furthermore, in the gap analysis of the present study, it was assumed that all committed actions would be fully implemented. An additional consideration is the growing concern about rebound effects, such as spending money saved from "avoid" actions on other carbon-intensive consumption activities [54,55], which were not considered in this study. Previous evaluations of carbon footprint calculators reported limited effects on the actual reduction of carbon footprints [22,56]. These previous results could be attributed to a combination of a lack of willingness to act, the attitude-behaviour gap, and possible rebound effects. The findings of the present study showed that the willingness to act, as demonstrated by the voluntary use of the carbon footprint calculator, is insufficient, even before the attitude-behaviour gap and its impact on actual footprint reduction.

Nevertheless, an encouraging finding is the existence of some progressive user segments willing to implement decarbonisation actions. The most progressive segment, '*lifestyle change enthusiasts*', committed as many as 25 actions with a potential footprint reduction of 2.8 tCO$_2$e, and 51–75 % of this segment could potentially achieve the 2030 targets in

housing and mobility. Other segments, such as '*dematerialisation enthusiasts*', '*sustainable diet enthusiasts*', and '*energy savers*', showed a narrower scope in their commitments, focusing primarily on food, goods/services, or housing. This highlights the need to leverage users' willingness to act in specific domains as an entry point to encourage the adoption of more holistic lifestyle changes. To address this large gap, effective actions may need to be mainstreamed across the population. The existence of the '*efficient environmentalists*' segment, which prioritises actions with higher mitigation potentials, is promising, but this user segment is small, accounting for only 7 % of users. There is thus a need to encourage other users, particularly those less likely to prioritise high-potential actions (e.g. user segments other than '*lifestyle change enthusiasts*' *and* '*efficient environmentalists*' and which have demographic characteristics of being middle-to-older-aged females and elderly males), to focus on carbon footprint information and take significant actions to reduce their carbon footprints.

The comparison of remaining carbon footprints suggests different reasons for the target-achievement statuses across domains. In the mobility and housing domains, where Scope 1 (direct emissions) and 2 emissions (indirect emissions from electricity) are predominant, over 99 % of users could achieve the target if they fully implemented the recommended actions, indicating that the gaps were primarily due to a lack of willingness or ability to act. In contrast, in the food and goods/services domains, where Scope 3 emissions (indirect emissions from other products and services) predominate, 84 % and 49 % of users, respectively, would still overshoot the target, even if they fully implemented the recommended actions. This suggests that the gaps were not only due to a lack of willingness to act, but also to the insufficiency of the recommended actions. There is thus a need to increase the availability and accessibility of decarbonisation options for consumers, especially for actions related to Scope 3 emissions in food and goods/services domains.

5.4. Improved use of carbon footprint calculators towards climate goals

The insufficient voluntary commitments observed in the present study highlight the need to expand the capabilities and application of carbon footprint calculators by explicitly incorporating target-oriented framing, tailoring features for different user segments, and facilitating systemic changes. While the importance of climate targets was introduced at the beginning of the calculator's use, the framing during the action selection process focussed on encouraging users to commit to as many actions as possible. In contrast, some citizen-thinking lab studies adopt a different approach by explicitly providing users with personal carbon footprint targets based on the 1.5-degree climate goal and encouraging the selection of actions to create target-achieving roadmaps [21,26]. A notable exception is a Swedish calculator that includes a voluntary target-setting function, a feature that is still uncommon in most footprint calculators [22]. To enhance their effectiveness, carbon footprint calculators could integrate improved messaging or gamification strategies to motivate participants to pursue personal footprint targets. Incorporating more target-oriented framing and features could better support users in aligning their actions with climate goals.

Another improvement could be to tailor messaging and functions to different user segments. The analysis in this study revealed significant heterogeneity in type, domain, and number of actions committed across demographic groups and user segments. However, most carbon footprint calculators, including the one used in this study, employ a unified design, offering the same messaging and functions to all users. Given the diverse commitments and characteristics of users, customising messages and functions for specific user segments could enhance engagement and effectiveness. As discussed in previous subsections, such tailoring could address different phases of user engagement, including taking initial actions after calculating their footprints, prioritizing higher-impact actions, expanding the scope of consumption domains, and committing to sufficient actions to meet climate targets. To achieve this, a stage-based

psychological framework that considers heterogeneity in decision-making phases (e.g. predecisional, practical, actional, and post-actional) could provide valuable guidance for designing more user-centric calculators [57].

Given the limited agency of individuals in taking action, there is ongoing debate about the emphasis on individual versus systemic change. However, it is clear that both are necessary, and that individuals can play multiple roles in facilitating systemic changes [58–62]. Low-carbon behaviours are not only influenced by internal factors, such as attitudes and normative goals, but also by external factors, such as financial and physical constraints [49]. Some calculator studies argue that a more balanced approach to communicating both individual and systemic changes is needed, as emphasising individual actions may create a sense of helplessness. Users themselves have indicated a need for supportive policies, such as incentives and regulations [21,38]. However, implementing supportive policies requires political acceptance, including public support, which makes it a complex challenge. Carbon footprint calculators could potentially be utilised to increase public support for mitigation policies. Previous studies highlighted that factors such as personal responsibility for climate change, the salience of past behaviours, and connection with personal values and identity are all critical for increasing acceptance of climate policies like carbon taxes [62–64]. These factors could potentially be strengthened through well-designed carbon footprint calculators. Nevertheless, the impacts of carbon footprint calculators on policy support remains unexplored, warranting further research [9].

Procedural justice, including participation and transparency, is crucial for increasing acceptance of mitigation policies [65]. Citizens play roles not only as consumers, but also as organisers and investors, roles that are often overlooked, even among affluent populations [66]. By providing a quantitative understanding of the impacts of citizens' lifestyles across the entire system, footprint calculators could serve as valuable tools for enhancing engagement in policymaking and planning processes. While some previous thinking lab studies have already explored this approach [21,24,26], few have explicitly integrated it into policymaking. Using carbon footprint calculators in participatory policymaking processes, such as national or regional climate citizens assemblies, represents a promising application area.

6. Conclusions

This study investigated the characteristics of self-committed actions using carbon footprint calculators and the gaps from mitigation targets, based on data from over 7000 users of a Japanese carbon footprint calculator. We quantified the gaps between self-committed actions and the targets derived from climate goals, revealing considerable shortfalls even among the most progressive user segments. The multivariate statistical analyses focusing on user segments, demographics, and types of actions highlighted the substantial heterogeneity in user engagement levels and the types of actions most frequently committed to by calculator users; findings that extend beyond the scope of previous studies on carbon footprint calculators. Our findings provide practical implications for improving the use of footprint information. They include promoting high-impact actions, facilitating spillovers across different consumption domains, implementing targeted interventions based on user segments and demographics, and using carbon footprint calculators in participatory processes to increase policy support. Such approaches can drive systemic changes that enable actions requiring financial investment and substantial lifestyle changes.

The limitations of this study are as follows. First, this study does not account for actual behavioural changes, and thus, attitude-behaviour gaps were not considered. Also, this study focused on self-commitment to actions, but public commitment was not analysed due to data availability. Furthermore, the user data in this study were not randomly sampled, but rather consist of self-selected users likely to represent a pro-environmental subpopulation. The variables considered in the

statistical analysis and profiling of segments were limited to those recorded in the user data. Consequently, other demographic factors, such as education, income, occupation; internal factors, such as motivation and values; and external factors, such as financial and physical constraints, were not analysed. Investigating the influence of these factors requires a combination of other methodologies, such as user surveys or interviews. Other technical limitations involve data quality. Although we limited the analysis to user data with valid responses to demographic questions and performed data cleaning for the footprint data, low-quality responses may still be present in the analysed data.

Another consideration is the external validity of results. The user data for this study was collected within a specific period (2022–2024) and geographical context (Japan), which undoubtedly influenced the results. Therefore, the results of this study may not necessarily be fully generalisable to other regions or time periods. Furthermore, due to the study's non-experimental design, the results should not be interpreted as causal effects of using a calculator. Instead, the statistical analyses reflect trends among heterogeneous users, offering insights into the extent of user engagements and types of committed actions.

This study represents an initial step in examining user segments and mitigation gaps using footprint calculators, and there are several areas for future research. Building on the findings of this study, improving the calculator, such as by considering user segments to promote engagement or stimulating spillover across consumption domains, is an important area for future research. Focusing on the attitude-behaviour gap, evaluating the effectiveness of carbon footprint calculators in affecting actual behavioural changes, and the role of psychological factors also remain to be investigated. Such analyses should not just focus on average users, but cover the heterogeneity of potential users; for example, the findings of this study highlighted the very different profiles and preferences of the different user segments. Moreover, given the significant mitigation gaps in personal carbon footprints, future research could explore ways to leverage footprint information to facilitate systemic changes beyond individual actions. This could include investigating the effects of footprint calculators on policy support, using footprint calculators in participatory scenario-making processes, or examining the systemic barriers to decarbonised actions within each consumer segment.

Declaration of competing interest

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

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.erss.2025.103930.

Data availability

The authors do not have permission to share data.

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