Building and Environment 287 (2026) 113918

Contents lists available at ScienceDirect

Building and Environment

journal homepage: www.elsevier.com/locate/buildenv

Occupants' willingness to share information for improved comfort and energy efficiency in offices

Marcel Schweiker [a,b,1,*], Dimitris Potoglou [c,1], Farah AlAtrash [d], Eleni Ampatzi [e], Maíra André [f,g], Elie Azar [h], Karol Bandurski [i], Leonidas Bourikas [j], Carolina Buonocore [k], Bin Cao [l], Giorgia Chinazzo [m], Rania Christoforou [a], Sarah Crosby [n,o], Renata De Vecchi [f], Edyta Dudkiewicz [p], Ricardo Forgiarini Rupp [q,r], Stephanie Gauthier [s], Natalia Giraldo Vasquez [q], Runa T. Hellwig [t,u], Gesche M. Huebner [v], Marta Laska [p], Marín-Restrepo Laura [w], Isabel Mino-Rodriguez [x], Mohamed M. Ouf [y], Romina Rissetto [x,z], Philip Turner [s], Yijia Wang [l]

[a] *Healthy Living Spaces Lab, Institute for Occupational, Social and Environmental Medicine, Medical Faculty, RWTH Aachen University, Aachen, Germany*
[b] *Chair of Healthy Living Spaces, Faculty of Architecture, RWTH Aachen University, Aachen, Germany*
[c] *School of Geography and Planning, Cardiff University, Cardiff, UK*
[d] *School of Architecture and Built Environment, German Jordanian University, Amman 11180, Jordan*
[e] *Welsh school of Architecture, Cardiff University, Cardiff, UK*
[f] *Laboratory of Energy Efficiency in Buildings, Federal University of Santa Catarina, Florianópolis, Brazil*
[g] *IEQ Lab, School of Architecture, Design and Planning, The University of Sydney, Australia*
[h] *Civil and Environmental Engineering Department, Carleton University, Ottawa, ON, Canada*
[i] *Institute of Environmental Engineering and Building Installations, Faculty of Environmental Engineering and Energy, Poznan University of Technology, Poznan, Poland*
[j] *Sustainability and Climate Change Consultant, UK*
[k] *Department of Architecture and Urban Planning, State University of Maranhão, Brazil*
[l] *Department of Building Science, School of Architecture, Tsinghua University, Beijing, China*
[m] *Controlled, Adaptive and Responsive Environments (CARE) Laboratory, Department of Civil and Environmental Engineering, Northwestern University, Evanston, USA*
[n] *School of Architecture, Civil & Environmental Engineering, École Polytechnique Fédérale de Lausanne, Switzerland*
[o] *Chair of Architecture and Building Systems, ETH Zürich, Switzerland*
[p] *Faculty of Environmental Engineering, Wroclaw University of Science and Technology, Poland*
[q] *International Centre for Indoor Environment and Energy, Department of Environmental and Resource Engineering, Technical University of Denmark, Kgs. Lyngby, Denmark*
[r] *Knowledge Centre on Daylight, Energy & Indoor Climate, VELUX A/S, Hørsholm, Denmark*
[s] *Faculty of Engineering & Physical Sciences, University of Southampton, Southampton, UK*
[t] *Chair of Building Physics, Faculty VI Planning Building Environment, TU Berlin, Berlin, Germany*
[u] *CREATE, Human Building Interaction, Aalborg University, Aalborg, Denmark*
[v] *European Centre for Environment & Human Health, University of Exeter, UK*
[w] *Architecture et Climat, Louvain Research Institute for Landscape, Architecture, Built Environment (LAB), Université catholique de Louvain, Louvain-la-Neuve, Belgium*
[x] *Building Science and Technology Group, Karlsruhe Institute of Technology, Karlsruhe, Germany*
[y] *Department of Building, Civil, and Environmental Engineering, Concordia University, Montreal, Canada*
[z] *Instituto Tecnológico de Buenos Aires (ITBA), Buenos Aires, Argentina*

ARTICLE INFO

Keywords:
Willingness to share data
Energy efficiency
Office buildings
Data privacy

ABSTRACT

Background: Human environmental perception and occupant behaviour are influenced by a multitude of factors, including demographic variables and individual preferences. Advancements in data collection allow the acquisition of extensive personal information, such as heart rate, skin temperature, and emotional responses to environmental conditions. These data can enhance research on multi-domain influences and on optimizing building operations but raise questions regarding individuals' willingness to share personal information.

* Corresponding author at: Healthy Living Spaces lab, Institute for Occupational, Social and Environmental Medicine, Medical Faculty, RWTH Aachen University, Aachen, Germany.
E-mail address: mschweiker@ukaachen.de (M. Schweiker).
[1] Shared first authorship

https://doi.org/10.1016/j.buildenv.2025.113918
Received 29 March 2025; Received in revised form 24 October 2025; Accepted 27 October 2025
Available online 28 October 2025

Public preferences
Workplace

Methodology: This study investigates how factors like data type, data collector, and anonymity level are associated with occupants' willingness to share information for improved indoor environmental conditions or energy efficiency. A stated preference discrete choice experiment was developed and applied, with responses collected from participants in 29 countries, resulting in a dataset with 791 samples. The discrete choice analysis was conducted using mixed logit models and based on Random Utility Theory.
Results: The outcomes indicate that respondents exhibit relative indifference toward sharing demographic and physical environmental data, while having heightened concerns about sharing psychological and activity-related information. Anonymity and control over the data appear to be of crucial importance. Additionally, data collection by academic institutions is preferred to that by for-profit entities. Variability in willingness to share data across and within samples of countries suggests a necessity for tailored strategies.
Impact: This research underscores the necessity of balancing advancements in energy efficiency and thermal comfort with societal needs that respect individual rights. Practical recommendations for effective personal data collection are provided and methodological limitations due to scenario complexity and participant engagement are highlighted.

1. Introduction

The average office worker spends over 90,000 h within their lifetime in office buildings [1]. Although the rise of remote working may alter this value, the creation of comfortable and energy-efficient office conditions remains of paramount importance [2]. Creating such conditions represents a multi-dimensional challenge that necessitates a deep understanding of several factors that occur simultaneously and drive occupant environmental perception and behaviour [3,4]. These factors typically include thermal, visual, and acoustical environmental parameters, but may also include personal as well as demographic information [2,5]. Many recent studies investigated the possibility of improving indoor conditions using new and continuous data streams coming from building automation systems (BAS) [6], or new sensors and wearable devices sharing a wealth of data related to occupant perception and physiology [7,8]. The type and amount of data that can be collected from building occupants has also increased significantly in recent years [8], encompassing personal information such as heart rate, skin temperature, and emotional reactions to environmental conditions [9]. Research is also progressing based on a hypothesis that more data will become available and could be used for controlling and managing indoor environments [10].

Access to such data on building operations and on occupants presents many potential benefits for research on multi-domain influences, active interfaces, and operation/control purposes [10]. For instance, smart thermostats require occupancy data to learn the users' schedules and thermal preferences, adjusting indoor settings to maximize thermal comfort while reducing energy loads [6]. Similarly, the development of personal thermal comfort models supported by wearable devices (e.g., smart watches) could help predict and improve comfort at the individual (rather than group) level [11]. However, a critical question regarding the availability of such data for building operation revolves around occupants' willingness to share (WTS) their personal information [12,13]. In this context, it is critical to acknowledge that many previous studies in the field assume the availability of personal data [10], which may not materialize due to growing awareness of privacy concerns. Obtaining feedback from occupants and sharing personal data could compromise privacy and sense of security [13].

To these ends, it is crucial to question whether the scenarios envisioned by researchers are realistic. Will occupants be willing to share their data in the manner proposed? This research aims to understand occupants' attitudes towards engaging in building performance improvement by sharing personal data. Through a unique survey that features a stated preference discrete choice experiment, a large international sample ($n = 791$) is collected to evaluate the willingness to provide data through automatic dedicated monitoring systems or through personal devices like smartphones or wearable devices.

2. Influences on the WTS personal information according to the literature

Information privacy concerns have been investigated by researchers since the 1970s and there are at least a few syntheses of these efforts [14,15]. The WTS personal data has been explored in various contexts, including big data approaches for customers and marketing, health-related data, as well as decisions on sharing personal data with commercial businesses [15]. Based on existing literature summarised in the supplementary material, the influences on the WTS found in the literature were grouped into eight attributes, of which benefit, the type of data collected, the data collector and users, and personal control over the data, were the most important ones (more details are available in the supplementary material).

The benefit of sharing data, such as monetary benefits or extra services, was one of the most important attributes for WTS for consumer choices [16], for health care purposes [17], but also for energy related aspects [18]. At the same time, Maier et al. [18] who looked at the WTS energy data of an Austrian sample found that although benefits from sharing data on an online platform was a decisive factor, when privacy concerns were raised, adding a personal benefit did not increase the WTS data. A study from Malaysia by Yussof et al. [19] revealed that participants were willing to share their electric energy consumption regardless of the technology used to collect the data, knowledge of personal data protection rules, and economic rewards, such as reduced electricity bill. A European survey found a higher WTS personal data to improve energy efficiency in the Nordic countries when compared to the other EU countries [20]. In contrast, a report based on face-to-face interviews of 27,498 respondents coming from all 29 European countries concluded that the category of personal information which Europeans are most likely willing to share about was "to improve medical research and care" [21]. But, in second place was the category "not willing to share any personal information for any purposes", followed by "to improve the response to crisis situations" and "to improve public transport and reduce air pollution" categories. "To improve energy efficiency" was the least likely category for sharing personal data, excluding "For other purposes" and "Don't know" categories.

The type of data collected was an important factor for consumers [16]. Li et al. [22], who explored privacy-related factors in smart office buildings through occupant interviews, found occupants to be unaware of the privacy risks posed by seemingly innocuous sensors, but focusing primarily on audio/video data risks. In the same direction, Harper et al. [23] highlight the lack of occupants' awareness of the type of data collected in commercial smart buildings. Some of the reasons for this unawareness were limited technological knowledge, unfamiliarity with the devices (inability to differentiate between a fake or a real sensor), the absence of a user interface, and unclear data collection process.

The data collector and users played an important role on several occasions. A higher WTS health-related data occurred for state/local public health authority compared to out-of-hospital providers [24].

Also, most users were found to have a high WTS their personal health care data for scientific research [17]. Trust of data users was an important factor for WTS for consumers [16]. In contrast, Schudy and Utikal [13] found no influence on the WTS with socially close compared to distant data users, but a decrease in WTS with an increasing number of data users.

Personal control over the data was also one of the most important attributes for consumers [16]. In a broad context considering the WTS personal data, a previously mentioned study in Europe concluded that "more than 4 in 10 Europeans would like to take a more active role in controlling the use of their personal information" [21].

3. Legal aspects

With the development of network information, people pay more and more attention to the security of personal information. Many countries and organizations have also issued relevant rules to protect people's information security. These rules or laws may also affect how people share their personal data. For European contexts, the Convention for the Protection of Individuals regarding Automatic Processing of Personal Data (Convention 108) sets out general principles, and the Directive 95/46 and GDPR (General Data Protection Regulation) elaborate a detailed legal regime for data protection [25]. Many countries have introduced their own data protection laws, while some have also set up special data protection authorities. Such action is happening in Europe [26], but also beyond. For instance, at least five of the twenty major Latin American countries have Data Protection Authorities [27]. There may also be specific regulations for certain types of data. The Global Alliance for Genomics and Health (GA4GH) has established nine fundamental principles for ethical health information sharing [28]. At the same time, there are legal constraints on cross-border information sharing. The European Economic Area (EEA) and certain other countries have mutually agreed to recognize each other's level of data protection as adequate. This means it is as straightforward to transfer data between the EEA and significant research partner countries, such as Japan and Switzerland, as it is to transfer data within the EEA [29].

4. Objectives and research questions

Despite few studies assessing the WTS information in distinct contexts, we do not know to what extent people are willing to share personal information for improvements of comfort and energy usage in office settings. Therefore, the objective of this study is to identify the main factors associated with consenting to sharing personal information for office building operation purposes. This inquiry is unique to the field of built environmental research but also compared to previous approaches regarding WTS because the benefit – one of the most important factors in previous studies on the WTS – is either difficult to quantify (in terms of comfort improvements) or not directly deliverable to the person sharing data (in terms of energy costs paid by the employer).

The overarching research question is: Which (personal) information are occupants willing to share, and under which conditions? This question encompasses two primary research questions (PRQs):

- PRQ1 – How is WTS associated with the type of data collected?
- PRQ2 – To what extent is WTS associated with the entities collecting or using the data, the level of anonymity, and the control over the data (level of autonomy)?

Further, three secondary research questions (SRQs) will be addressed.

- SRQ1 – Which benefits (direct/indirect) motivate participants to share personal information?
- SRQ2 – What frequency of data collection is considered acceptable?
- SRQ3 – What method of collecting personal data are participants more willing to accept?

Furthermore, regional differences will be considered where applicable, as cultural and legal aspects concerning data sharing may vary across countries and thus impact many aspects of WTS. *This study serves as a proof-of-concept exploring patterns in occupant preferences across a diverse international sample of office workers through discrete choice experiments.*

5. Materials and method

To address the research questions stated in the previous section, this study developed and implemented a stated preference discrete choice experiment (SPDCE) as part of an online survey questionnaire. The strength of SPDCEs method is that it is particularly suited to examining how individuals simultaneously evaluate and trade-off across different attributes (characteristics) when they consider different products, services, policies, courses of action or situations [30]. This is an advantage over simpler preference elicitation methods or traditional panel surveys, which usually lack detailed context and explicit trade-off analysis. Such instruments collect 'single-dimension' opinions (e.g., yes vs. no; strongly agree – strongly disagree), thus involving the risk of obtaining ideological responses. Also, Likert-scale type questions tend to measure perceptions regarding the 'control of information' and 'intention to disclose' in relation to antecedents such age, gender, etc. The 'stated intention to disclose' remains a single-dimension response within limited context (and variation) on 'what', 'to whom' and 'for how long' to disclose - see, also [31] for a detailed discussion on the same.

The SPDCE method is therefore in line with the scope of this study – i.e., to simultaneously capture what conditions of a typical working-space occupants would choose when these involve the simultaneous collection of an array of personal information, in exchange for thermal comfort. The analysis of the collected choices allows examining how occupants (positively/negatively) 'weigh' each type of personal information requested and thus helps reveal nuanced trade-offs participants would make when deciding to share personal data. SPDCEs have been successfully applied in many contexts in which the aim was to study the trade-offs between privacy risks/costs and benefits, the so-called Privacy Calculus [32]. For example, Potoglou et al. [33] and Patil et al. [34] examined the trade-offs between privacy and travel safety in the UK and across Europe, respectively. Also, Potoglou et al. [35] explored Europeans' preferences for internet surveillance in exchange for privacy-enhancing services and Potoglou et al. [36] examined the role of privacy concerns on consumers' intentions to use e-commerce in the UK.

However, to the knowledge of the authors, no application of this method within the built environment research has been previously published; thus, this study also serves as a proof-of-concept for the application of this method in this subject area. Additional survey items were added after the SPDCE in relation to the secondary objectives (see Section 4). All materials are available at https://osf.io/tmcjz/, which includes a registered pre-analysis plan [37].

5.1. Design of the stated preference discrete choice experiment and survey

This study developed a unique version of SPDCEs adjusted to the area of built environment based on applications in other disciplines [34,35], a review of related literature, and the authors' domain knowledge.

The design of the SPDCE firstly involved the definition of the alternatives, attributes describing each alternatives and the attributes levels – i.e., the possible values that each attribute could realistically take. As shown in Fig. 1, the choice experiment involved two unlabelled alternative options (Scenarios A and B), each reflecting the conditions of a typical office-based workspace and the collection of different levels of personal data and space-related information. Respondents were advised that they could also choose none of the scenarios on offer thus allowing a)

Description	Scenario A	Scenario B
What information is collected		
Demographics (e.g. age, gender)	✓	✗
Psychological parameters through follow up survey questionnaires (e.g. personal preferences and attitudes)	✗	✗
Physical parameters (e.g. room temperature, noise level, illuminance)	✗	✗
Activity monitoring (e.g. presence, interaction with windows)	✗	✓
Physiological data (e.g. heart rate , body temperature)	✓	✗
Who collects and controls the data		
Responsible organisation for data collection and primary use	Government Department	University / Research Institution
Level of anonymity	You cannot be personally identified	You can be personally identified by those having access to the data
Level of autonomy	No control over your own data	View your own data
Secondary use of the data by third party organisations	None	Market research

b)

Scenario A	Scenario B	Neither scenario
○	○	○

Fig. 1. a) Example choice card and b) options to choose.

for ‘unforced choices’.

Each alternative was described by a set of nine (9) attributes, each reflecting information collection by devices and/or computer-based surveys in each scenario, which could be used to adjust the indoor environment and improve the respondents’ comfort level. The selection of these attributes and levels was guided by the literature review presented in the supplementary material, which focused on the key factors in related choice contexts, and workshops among the research team [37]. These attributes corresponded to wider individual concerns about organisational information practices such as (type) of personal information collected, handling (and errors), and secondary use [32]. Most of these attributes are generally common with relevant previous studies in other subject areas (e.g., [35]. As shown in Table 1, the first set of attributes corresponded to the ‘type of data collected’ (PRQ1) and the second set of attributes on ‘the context of data collection’ (the data collector and user, the level of anonymity, and the level of autonomy (PRQ2)). Prior to the main survey fieldwork, attributes and levels were further refined through a cognitive testing exercise with 12 participants [31].

The generation of the choice cards like the one shown in Fig. 1, was based on a D-efficient design matrix based on the multinomial logit model using the software Ngene [38]. The prior parameters to generate the experimental design matrix were estimated based on a first pilot study with 29 participants, which was conducted in Southampton, UK. The generated matrix included 60 choice cards in 12 blocks, so that it was possible to offer five choice cards to each respondent. Limiting each respondent to five choice cards was based on a trade-off across respondent fatigue, cognitive burden of the experiment, and statistical efficiency [39]. The presentation of the choice cards was followed by questions asking whether respondents understood the information presented to them.

As shown in Fig. 1, the choice experiment involved two unlabelled alternative options (Scenarios A and B), each reflecting the conditions of a typical office-based workspace. Each scenario proposed the collection of different levels of personal data and space-related information. The information could be collected by devices and/or computer-based surveys in each scenario to adjust the indoor environment and improve the respondents’ comfort level. Respondents were advised that they could also opt for “neither scenario”.

5.2. *Additional survey measures*

The second part of the survey included questions on selected personal information to examine how individual factors relate to

Table 1
Attributes and levels of the stated preference discrete choice experiment.

	Attribute Levels			
Attribute	0	1	2	3
Type of data collected				
Demographics (e.g., age, gender)	No	Yes		
Psychological parameters through follow up survey questionnaires (e.g., personal preferences and attitudes)	No	Yes		
Physical parameters (e.g., room temperature, noise level, illuminance)	No	Yes		
Activity monitoring (e.g., presence, interaction with windows)	No	Yes		
Physiological data (e.g., heart rate, body temperature)	No	Yes		
Context of data collection (collector, control, usage)				
Responsible organisation for data collection and use	Government department	University / Research Institution	Not-for-profit organisation	For profit organisation
Level of anonymity	You can be personally identified by those having access to the data	You can be personally identified by the data collector only	You cannot be personally identified	
Level of autonomy	No control over your own data	View your own data	View and delete your own data	View, delete, and choose what and how often your own data can be collected
Secondary use of the data	None	Market research	University research	Governance and policy making (e.g., tax savings)

respondents' choices. These questions incorporated: (1) age, (2) type of work, (3) occupation, (4) qualification, (5) satisfaction with current personal financial condition, and (6) description of current and previous area of residence.

The third part consisted of self-administered statements regarding data sharing by expressing the level of consent with each statement. Participants also expressed the level of agreement to use and share personal data collected at the workplace under differing conditions.

5.3. Survey implementation

The survey and all other materials, including participant information, informed consent statement and data protection notes, were translated from the base English version to Arabic, Chinese, Danish, French, German, Greek, Italian, Polish, Portuguese, and Spanish. All translations and reviews were carried out by native speakers, having a main translator and a second person to review it. Further details are outlined in the report of our second pilot cognitive study [31]) which applied the same translation protocol in order to ensure that the context is preserved to the extent possible and that the person answering the question will be able to interpret it correctly. Additionally, the pilot phase served for further verifications. Ethics approvals were sought from national or local ethic boards by authors as needed. Positive votes were obtained from Concordia University (Canada), Lancaster & Southampton University (UK), Wroclaw University of Science and Technology (Poland) and UFSC (Brazil). Exemptions were obtained from the ethic boards of University Hospital RWTH Aachen (Germany), University College London (UCL) (UK), Cardiff University (UK) and National University of Singapore (NUS) (Singapore). The final versions were implemented in the Qualtrics survey platform.

Following thorough internal reviews and testing of the implementation, data collection followed two distinct tracks. For the first track leading to a convenience sample, the survey was announced through social media, mailing lists, electronic news bulletins to administrative and library staff, personal contacts of the authors, sent directly to people working in befriended companies like IT company, AI Systems workshop, design office, and Local Authorities, free messaging and calling apps, and via links on staff members' websites. In Poland it was also possible to advertise the information about this study in the industry journal Rynek Instalacyjny. In this track, participants did not receive any payment but could select one of three organizations that the authors donate to after the respondent's participation. In the second track, representative samples from Germany and US with a target sample size of 250 respondents (1250 choice observation) each were collected via the provider Prolific. These respondents were paid for their participation 21.70 British Pounds per hour for the German sample and 23.08 British Pounds per hour for the US sample.

The distribution of the questionnaire through all available channels started in the middle of September 2022 and finished in October 2023.

5.4. Data processing and analysis

The analysis of the collected data primarily focused on respondents' choices in the experiment. Firstly, a series of data validity checks were conducted against several exclusion/inclusion criteria (see supplementary materials for more details). To perform statistical analysis, only countries with sufficient sample size were assessed individually, and all countries were included in the "complete dataset". Based on our argumentation in the pre-analysis plan [37], based on [40], and the second pilot study [31], the minimum sample of 100 was identified as necessary for this analysis and achieved for two countries (United States and Germany). The initial sample from Poland also achieved this target but was reduced to 88 responses after data cleaning. Although lower than suggested, the individual analysis of Polish sample was maintained after verifying non-significant differences in the results of the full and the reduced sample.

The analysis of stated choice experiment data was conducted using discrete choice analysis based on Random Utility Theory [41]. This approach helps identifying the 'weights' respondents placed on the different attribute levels describing each scenario and thus, the probability of choosing a scenario or the 'None' options. Each attribute shown in Table 1 was dummy coded so that the effect (weight) of each attribute level is estimated relative to a reference level. For example, the 'Demographics' was dummy coded so that the model estimated the effect of 'Yes' relative to 'No'. Similarly, for a four-level attribute such as 'Secondary use of data', the effect of 'Market Research' was estimated relative to the reference case 'None' – i.e., no secondary use of data. The assumption is that respondents assess the alternative options offered in the experiment (Scenario A, B and None) and choose the one with highest utility [42].

Random parameters logit (or Mixed Logit) models were estimated separately for each country sample, namely US, Germany and Poland.

An additional model was estimated for the complete dataset and added to the supplementary materials as the imbalance in samples across countries does not permit further interpretation. These models help estimate the mean parameter estimates for each dummy-coded attribute level, and the standard deviation of each (normally distributed) attribute-level parameter. In effect, random parameter models help capture unobserved taste heterogeneity in respondents' choices within each country and also control for the serial correlation due to the repeated observations obtained from each respondent. Under random-utility-modelling, a respondent i facing a choice situation (card) t would assign utility U_{ijt} for alternative j and this utility is specified as:

$$U_{ijt} = V_{ijt} + \varepsilon_{ijt} \tag{1}$$

Where V_{ijt} is the deterministic component of the utility U equal to:

$$V_{ijt} = \mathbf{X}_{ijt} * \beta_i \tag{2}$$

and

ε_{ijt} is the error term which incorporates unobserved effects linked with the choice made when a respondent faced choice card *t*.

In a MXL model, $\boldsymbol{\beta_i}$ is an individual coefficient matrix corresponding to the weights of attribute levels **X** and is equal to:

$$\beta_\mathbf{i} = \beta + \eta_i \tag{3}$$

Where $\boldsymbol{\beta}$ comprises the average effects (weights) of attribute levels across all respondents and η_i is a matrix capturing the individual specific deviations (standard deviations) with mean zero and standard deviation matrix **Σ.** $\boldsymbol{\beta_i}$ is fixed across all choice cards *t* shown to respondent *i*, and thus captures the correlation across the repeated choices for that respondent [43].

The interpretation of results depends on the significance of the mean coefficient and their standard deviation. If both are significant, this indicates an average preference for or against the option compared to the reference, while also reflecting variability in preferences across respondents, i.e., taste heterogeneity. This variability suggests that some respondents may hold differing or even opposing preferences, potentially indicating subgroups with differing views. If the standard deviation is significant but the mean coefficient is not, this points to heterogeneity in preferences without a clear overall tendency, possibly reflecting polarised opinions. When the mean coefficient is significant, but the standard deviation is not, this implies a consistent preference across respondents, suggesting general agreement. Conversely, if neither the mean coefficient nor the standard deviation is significant, this points to a homogeneous indifference, with little variation in responses, implying alignment in that indifference. The models were estimated for the United States, Germany, Poland and the complete dataset (results from the "complete dataset" are presented in the supplementary materials). Significance is defined by p-values lower than 5 % and 10 % is considered circumstantial significance. In the results section, only the MXL is presented as it contains the summary of coefficients and variance with the same trends as the MNL.

While the models provide robust insights into general trends, their design does not allow for direct comparisons between countries or between attributes. To address these limitations, ranking and Likert-scale questions were used to examine participants' motivations to choose a card regarding included attributes, data control and use, providing additional context to interpret the models' results. The Cronbach analysis of the Likert-scale questions confirmed acceptable consistency (alpha = 0.71). Therefore, to further understand cross-country differences and attribute-specific patterns, we conducted a Kruskal-Wallis test, a non-parametric test suitable for comparing three or more groups with ordinal data, followed by post-hoc Dunn tests for all questions. Additionally, a Chi-squared test for independence was conducted for the Likert-scale questions to examine the association between countries and levels of agreement.

6. Results

6.1. Descriptive analysis

As a result of data processing, the cleaned complete dataset consists of 791 samples. Table 2 presents sample characteristics across Germany, United States, Poland, the other 26 countries, and the complete dataset (all countries combined). Among the 26 other countries, Brazil contributed 32 responses, China 28, Denmark 20, Greece 16, the United Kingdom 14, and Italy 12. The remaining 20 countries each provided five or fewer responses. The dataset includes responses from all five continents, but the African sample totalled only 3 responses and the Australian sample 2. Overall, the sample includes 51 % women and 48 % men, and few non-binary or self-described genders. Most of the participants are between 30 and 49 years old (63 %) and the second largest group is between 18 and 29 years old (25 %). Most participants indicated to be professionals (50 %), clerical support workers (19 %), or technicians and associate professionals (10 %). In terms of level of education, most participants in the overall sample have a post graduate degree (39 %) or a university degree (41 %). However, when analysing the results by country, Poland and "Other countries" show a higher proportion of participants with a post graduate degree (82 % and 62 % respectively) compared to Germany and US (16 % and 26.1 % respectively).

Although 75 % of participants indicated to have never completed a choice card questionnaire before, 84 % indicated they understand the options presented and the choice card selection process. Regarding the choice cards' categories, 74 % indicated that all options were clear. Each category was unclear to at least one person, but the percentage of people indicating that for each category was small (from 1.8 to 8.3 % of the complete sample). The least unclear attribute was demographics (2 %), while the psychological parameter was the one receiving most votes (8 %).

6.2. Associations between WTS and selection of choice card scenarios

The main results of this study are presented in Table 3 with the values estimated for the **Mixed Logit Models (MXL)** for each country. Negative coefficients with significant p-values (<0.05) indicate that respondents would be less willing to share their data if that attribute or option was included. Positive coefficients with significant p-values, on the other hand, indicate that respondents would be more willing to share their data if that attribute was included instead of the reference case. It is worth noting that the model coefficients cannot be compared between attributes; comparison is only possible within an attribute. Therefore, a higher coefficient in one attribute compared to another does not necessarily imply a greater association with WTS.

As shown in Table 3 by the negative coefficients of the **Alternative Specific Constant 'Neither'**, participants across all country samples were more likely to engage in the experiment choosing scenarios "A" or "B" instead of "Neither". This point indicates that in general, they would have a preferred card choice and would avoid choosing none. However, the significant standard deviations of that attribute observed in all country samples highlight considerable taste heterogeneity in respondent behaviour. This finding suggests that while most respondents avoided the "Neither" option, a portion of them may have preferred it under certain conditions.

Regarding the **type of data collected**, all participants were indifferent to sharing their demographic information, though within the German sample, options that involved providing demographic information were chosen less often, an effect marginally significant at the 10 % levels, with non-significant standard deviations across most country samples except for the Polish sample, where some variation was observed. However, regarding other variables, differences between countries are noticed. The German dataset demonstrates lower WTS data related to activity, psychological and physiological data, although this

Table 2
Sample characteristics grouped by country – absolute number of responses and percentile by country.

Categories	Germany		United States		Poland		Other countries		Complete dataset	
Gender										
Female	126	52 %	117	49 %	55	63 %	102	47 %	400	50.6 %
Male	116	48 %	121	50 %	32	36 %	110	50 %	379	47.9 %
Non-binary / third gender	0	0 %	3	1 %	0	0 %	1	0 %	4	0.5 %
Prefer not to say	1	0 %	0	0 %	1	1 %	3	1 %	5	0.6 %
Prefer to self-describe	1	0 %	0	0 %	0	0 %	0	0 %	1	0.1 %
NA	0	0 %	0	0 %	0	0 %	2	1 %	2	0.3 %
Age (years)										
18–29	90	37 %	48	20 %	15	17 %	47	22 %	200	25.3 %
30–49	136	56 %	155	64 %	66	75 %	140	64 %	497	62.8 %
50–64	18	7 %	37	15 %	6	7 %	22	10 %	83	10.5 %
>65	0	0 %	1	0 %	0	0 %	5	2 %	6	0.8 %
Prefer not to say	0	0 %	0	0 %	0	0 %	3	1 %	3	0.4 %
NA	0	0 %	0	0 %	1	1 %	1	0 %	2	0.3 %
Level of education[a)]										
Full secondary	22	9 %	31	12.9 %	0	0 %	3	1.4 %	56	7.1 %
Other, please specify	3	1.2 %	5	2.1 %	8	9.1 %	14	6.4 %	30	3.8 %
Partial secondary	10	4.1 %	16	6.6 %	0	0 %	1	0.5 %	27	3.4 %
Post-secondary or polytechnic	13	5.3 %	15	6.2 %	1	1.1 %	4	1.8 %	33	4.2 %
Post graduate degree	39	16 %	63	26.1 %	72	81.8 %	135	61.9 %	309	39.1 %
Prefer not to say	3	1.2 %	6	2.5 %	1	1.1 %	1	0.5 %	11	1.4 %
University degree	154	63.1 %	105	43.6 %	6	6.8 %	60	27.5 %	325	41.1 %
Profession										
Clerical Support Worker	77	32 %	43	18 %	14	16 %	16	7 %	150	19.0 %
Manager	20	8 %	69	29 %	9	10 %	27	12 %	125	15.8 %
Other, please specify	10	4 %	8	3 %	4	5 %	17	8 %	39	4.9 %
Professional	104	43 %	96	40 %	56	64 %	142	65 %	398	50.3 %
Technician and Associate Professional	33	14 %	25	10 %	5	6 %	16	7 %	79	10.0 %
Total	244		241		88		218		791	

[a)] The education categories included in the background survey were adopted from work developed by the European Social Survey (ESS) [44] for harmonising educational qualifications. The resulting equivalencies selected into the various translations developed for this survey were further rationalised to match the expectations of participants who are unfamiliar with such classifications. At the analysis stage, we found that the levels of educational qualifications included in the different translations differed with respect to the bachelor's and master's degree assignments (See Table S2 in supplementary materials).

opinion is not consensual, and taste heterogeneity is observed for all attributes. Meanwhile, the US and Polish samples show opposed results and most data types are not homogeneously accepted or rejected. Polish respondents are homogeneously indifferent to collection of activity, while respondents in the other samples prefer not having it collected. The collection of physical parameters is indifferent for all country samples, but this opinion is not consensual for the US.

Regarding the **responsible organisation for data collection and its use**, all countries opted against it being managed by a for-profit organization and would prefer it to be managed by a university/research institution instead of a governmental department. All country samples except the US indicated no difference between government department and a not-for-profit organization, placing them as the second preferred option. The US respondents, instead, consider not-for-profit organization similarly to university/research institution. However, the level of agreement differs across the country samples. In Germany, the standard deviation suggests the only consensus is the preference for not-for-profit data management, while the preference for university and against for-profit organisation is not consensual, indicating varying opinions. Only in the US, universities are preferred over not-for-profit organizations and there is clear homogeneity in this preference over governmental departments, but the opinion against for-profit organization is not homogeneous, showing greater variation. The Polish sample shows complete agreement to all positions, against for-profit and preference for university management over government and not-for-profit organization. This means that in general, there is more alignment against for-profit organizations than a unified preference for university, government, or not-for-profit management of data.

For the **level of anonymity**, the mean coefficient indicates that the reference case, i.e., not allowing personal identification, was considered more favourably than the other options, which allow the identification by those accessing the data or by the data collector only. For the US and German dataset, consistent heterogeneity is observed, while for Poland, there is homogeneity in the preference for total anonymity instead of identification by the researcher and circumstantial heterogeneity for further identification by the data manager.

Regarding the **level of autonomy**, "view, delete, and choose what and how often your data can be collected" was considered equivalent to "view and delete your own data" on average across all country samples. For all country samples, these options were preferred by participants over having no control over their own data. However, the standard deviation indicates there is only agreement about this point in Germany and Poland. For the US dataset, opinions show greater variation regarding having no control over the data. Simple data visualization without the option to edit it was considered similar to the other control option for Germany and Poland, with a significant level of agreement.

In line with the outcome for the responsible organisation for data collection, a similar pattern is observed for **secondary use of the data**. Participants across all country samples are less willing to share their information if the data is also used for market research, as indicated by the negative and significant coefficients. However, the significant standard deviation in most country samples suggests variability in opinions, with Poland being the only country showing a consensual opinion against market use. On the other hand, Poland is the only country sample that shows consensual preference for data to be used for academic research instead of no secondary purposes. Germany and Poland seem indifferent to alternative use by policymakers, but that is not consensual for Germany, where some people might be against it. Similarly, the US dataset shows higher WTS data if not used by policy makers, but that opinion is not consensual.

6.3. *Further associations with WTS*

The analysis of the additional questions presented after the choice cards revealed the following observations.

Regarding the association of type of information is collected with

Table 3
Mixed logit model per country sample. Significant p-values, <0.05 darker green and bold, <0.1 light green and italic.

	Germany		US		Poland	
Parameter (mean)	Coef.	*p*	Coef.	*p*	Coef.	*p*
Alternative Specific Constant 'Neither'	**−3.177**	**0.000**	**−4.322**	**0.000**	**−2.502**	**0.002**
Type of data (collection of data vs. no collection)						
Activity monitoring	**−0.694**	**0.000**	**−0.855**	**0.000**	−0.271	0.399
Demographics	−0.254	0.052	−0.153	0.323	−0.154	0.645
Psychological parameters through follow up survey questionnaires	**−0.543**	**0.000**	*−0.285*	*0.089*	−0.413	0.177
Physiological data	**−0.806**	**0.000**	−0.192	0.177	**−0.974**	**0.012**
Physical parameters	−0.200	0.168	0.114	0.569	−0.254	0.400
Responsible organisation for data collection and use						
Government Department	Reference category					
University / Research Institution	**0.803**	**0.003**	**0.644**	**0.015**	**0.978**	**0.031**
Not-for-profit organisation	0.062	0.744	**0.538**	**0.027**	−0.150	0.741
For profit organisation	**−0.484**	**0.033**	**−0.648**	**0.011**	**−1.037**	**0.030**
Level of anonymity						
You cannot be personally identified	Reference category					
You can be personally identified by those having access to the data	**−1.275**	**0.000**	**−1.704**	**0.000**	**−1.943**	**0.001**
You can be personally identified by the data collector only	**−0.995**	**0.000**	**−1.265**	**0.000**	**−1.524**	**0.013**
Level of autonomy						
View, delete, and choose what and how often your own data can be collected	Reference category					
No control over your own data	**−1.036**	**0.000**	**−1.583**	**0.000**	**−1.504**	**0.038**
View your own data	−0.322	0.213	**−1.076**	**0.000**	0.057	0.904
View and delete your own data	−0.026	0.910	−0.075	0.769	−0.062	0.879
Secondary use of the data						
None	Reference category					
Market research	**−0.485**	**0.041**	**−0.988**	**0.000**	*−0.742*	*0.085*
University research	0.289	0.187	−0.101	0.660	**0.911**	**0.027**
Governance and policy making	−0.341	0.101	**−0.701**	**0.005**	−0.307	0.423
Standard deviation of estimated parameters						
Alternative Specific Constant 'Neither'	**0.982**	**0.000**	**−1.597**	**0.000**	**1.726**	**0.000**
Activity monitoring	**−1.251**	**0.000**	**1.666**	**0.000**	0.303	0.725
Demographics	0.078	0.477	−0.059	0.751	*1.331*	*0.060*
Psychological parameters through follow up survey questionnaires	**1.094**	**0.000**	**−1.173**	**0.000**	1.044	0.158
Physiological data	**0.891**	**0.002**	−0.364	0.303	*1.524*	*0.062*
Physical parameters	0.302	0.582	**−1.263**	**0.001**	0.985	0.124
University / Research Institution	**1.383**	**0.000**	−0.067	0.715	0.765	0.284
Not-for-profit organisation	−0.083	0.538	−0.813	0.084	0.941	0.226
For profit organisation	**0.975**	**0.024**	**−0.950**	**0.032**	0.667	0.234
You can be personally identified by those having access to the data	**−1.118**	**0.000**	**1.401**	**0.001**	*1.390*	*0.064*
You can be personally identified by the data collector only	**1.308**	**0.000**	**0.997**	**0.023**	1.178	0.192
No control over your own data	0.627	0.234	**1.419**	**0.001**	−2.017	0.103
View your own data	0.398	0.169	**−1.053**	**0.024**	−0.092	0.712
View and delete your own data	−0.048	0.906	−0.703	0.124	0.335	0.579
Market research	**−1.231**	**0.000**	**−0.868**	**0.027**	−0.336	0.653
University research	0.374	0.707	−0.225	0.716	−0.784	0.489
Governance and policy making	**−1.167**	**0.000**	**1.359**	**0.001**	−1.272	0.355
Sample size (individuals)	244		241		88	
Sample size (observations)	1220		1205		440	
Number of parameters	34		34		34	
LL(0)	−1340.3		−1323.8		−483.4	
LL(final)	−1144.5		−1050.5		−407.4	
Rho^2 (vs. equal shares)	0.146		0.207		0.157	
AIC	2356.9		2168.9		882.79	
BIC	2530.5		2342.1		1021.7	

scenario selection (PRQ1), Fig. 2 illustrates the ranked importance of demographic, psychological, physical, activity, and physiological data.

Demographic data was consistently ranked last (30–36 %) and consistently so across all countries (H(2) = 0.407, $p = 0.816$).

The importance of **psychological parameters** varied notably across countries. In Germany and Poland, this category was most frequently ranked in the first and second positions, indicating a strong association with WTS. In contrast, participants in the US ranked it primarily in the third and fourth positions, suggesting weaker association with scenario selection. These differences were statistically significant (H(2) = 33.1, $p < 0.001$), specifically between the US and both Germany and Poland (post-hoc $p < 0.001$).

Physical parameters were rarely ranked first or second, with preferences distributed more evenly across the third, fourth, and fifth positions, suggesting a weaker association between WTS and these attributes. These patterns were consistent across all countries, with no significant differences observed (H(2) = 0.872, $p = 0.647$).

Activity monitoring revealed distinct cross-country differences in rankings. Participants in the US predominantly ranked it first (43 %), while German respondents split their preferences between the first and second positions. In contrast, Polish participants mostly ranked it in the fourth and fifth positions. These differences were statistically significant (H(2) = 33.3, $p < 0.001$), with post-hoc tests confirming significant contrasts between all country pairs ($p < 0.01$).

Physiological data were more frequently ranked in the second and third positions, indicating a moderate level of importance. This pattern is consistent across all countries, with no significant differences (H(2) = 0.613, $p = 0.736$).

Related to PRQ2, Fig. 3 illustrates the ranked importance of attributes on scenario selection related to who collects and controls the data: responsible organisation for data collection and use, level of anonymity, level of autonomy, and secondary use of the data.

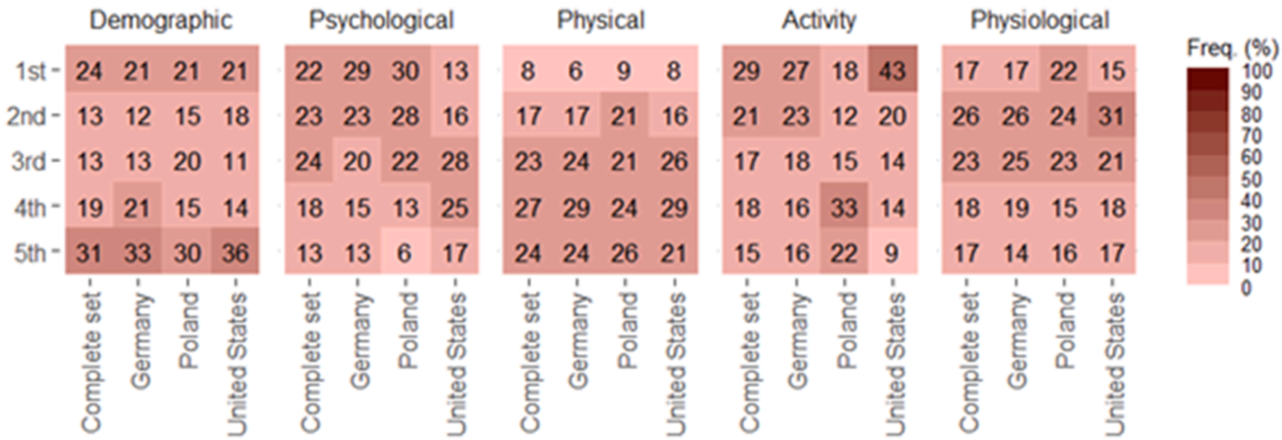

Fig. 2. Order of importance of type of information collected for scenario selection. Numbers represent percentage frequency of responses per country sample.

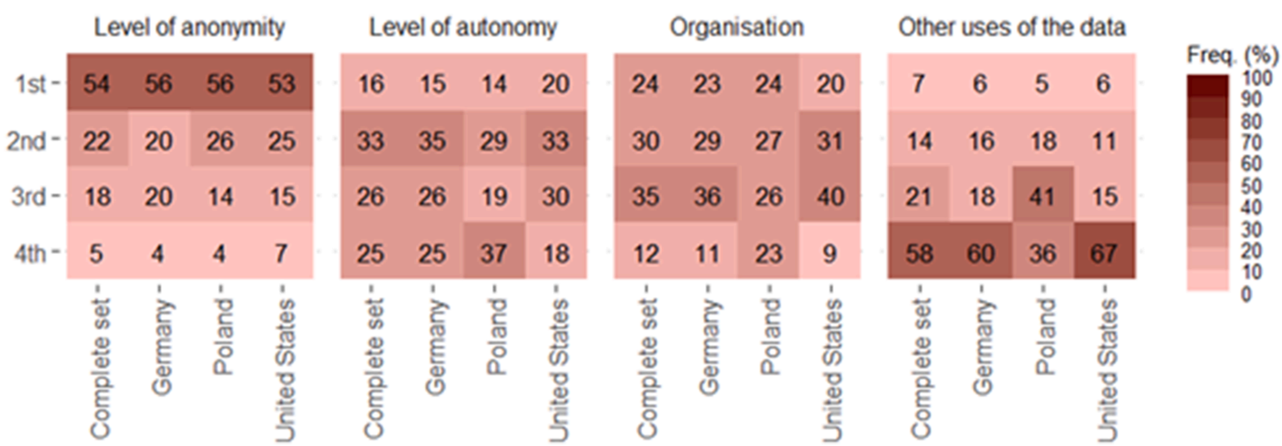

Fig. 3. Order of importance of data control for scenario selection. Numbers represent percentage frequency of responses per country sample.

Anonymity was consistently ranked as the most important attribute across all country samples (53–56 % ranked it first), with no significant differences between countries (H(2) = 0.452, p = 0.80).

In contrast, the level of autonomy showed greater variability, ranking second in Germany and the US but fourth in Poland. Statistical analysis confirms a significant difference in ranking across countries (H(2) = 7.02, p = 0.030), primarily between Poland and the US (post-hoc p = 0.035). Although Poland and Germany showed consistent preferences for maintaining autonomy and the US heterogeneity, the rankings reveal differences in the overall importance of autonomy across countries.

The responsible organisation for data collection and use ranked third across most country samples, despite some variation in preferences. Polish respondents did not show a clear trend. In the US, a similar proportion of participants ranked this attribute second and third, which might be associated with the smaller difference in preference between not-for-profit and university institutions observed in the model. However, these differences were not statistically significant (H(2) = 0.684, p = 0.71), and thus do not suggest any strong cross-country variation for

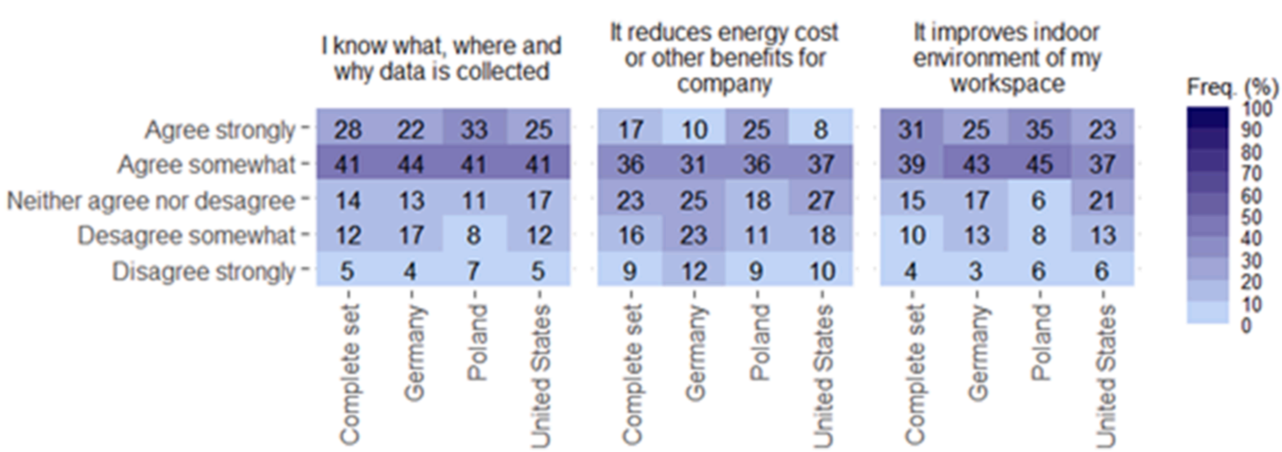

Fig. 4. Level of agreement to conditions for accepting sharing data based on its use. Numbers represent percentage frequency of responses per country samples.

this attribute.

Finally, the attribute secondary use of the data was consistently ranked least important in Germany and the US but slightly higher in Poland, where it was more frequently placed in the third position. Statistical analysis confirmed significant differences across countries (H(2) = 15.6, $p < 0.001$), specifically between Poland and both Germany (post-hoc $p = 0.014$) and the US (post-hoc $p < 0.001$). In contrast, participants in Germany and the US consistently ranked secondary use of data last.

Fig. 4 presents the cross-country responses regarding the acceptance of data sharing under different conditions. Responses were analysed for three key scenarios: (1) if participants could know what data is transferred and why (transparency), and, related to the benefit, (2) if data sharing resulted in reduced energy costs or other benefits for their company, and (3) if it improved environmental conditions in their workspace.

Most participants across all countries somewhat agreed that knowing what, where and why data is collected is important (41–44 %). Participants from Poland showed a slightly higher percentage of "Agree strongly" responses (33 %), although no significant differences were found between countries for this question (H(2) = 3.92, $p = 0.14$), indicating a consensual perception of the importance of transparency in data collection.

When asked if they would share data if it resulted in reduced energy costs or other benefits for their organisation, participants' responses varied significantly between countries (H(2) = 14.44, $p < 0.001$). Across all country samples, fewer participants agreed strongly compared to partial agreement ("Agree somewhat"), which was the most common response (31–37 %). Post-hoc tests revealed that Poland differed significantly from both Germany ($p < 0.001$) and the US ($p < 0.01$), while no significant differences were observed between Germany and the US. The Chi-square test confirmed these differences ($\chi2(8) = 24.99$, $p < 0.01$), with Polish respondents significantly more likely to "Agree strongly" ($r = 4.31$) and less likely to disagree compared to other countries, suggesting a higher association with WTS data if it benefits their company. In contrast, participants in the US were less likely to "Agree strongly" than other countries ($r = -2.06$).

Participants were also asked if they would accept data sharing if it improved environmental conditions in their workspace (e.g., temperature, air quality). Responses showed significant differences between countries (H(2) = 9.61, $p < 0.01$). Post-hoc tests revealed significant contrasts between Poland and the US ($p < 0.01$), while no differences were found between these countries and Germany. The Chi-square test confirmed these differences ($\chi2(8) = 18.65$, $p < 0.05$), with Polish respondents being significantly more likely to "Agree strongly" ($r = 2.24$) and less likely to choose "Neither agree nor disagree" ($r = -3.06$). Conversely, respondents from the US were more likely to remain neutral ($r = 2.30$). Across all country samples, a greater percentage of participants agreed strongly or somewhat with sharing data for improving their own workspace conditions (70–80 %) compared to benefits for the company (61–41 %).

Finally, regarding the frequency of data collection considered acceptable, more than half of participants (58 %) indicated they would likely accept sharing their data just once. In this question, a higher frequency was associated with a lower number of people willing to accept. Thirty percent would accept a monthly frequency, 23 % weekly collection, 17 % a daily collection, and 9 % multiple data collections per day. For highly frequent data collection, less invasive methods were accepted by a greater number of participants. In this multiple option question on data collection method, most participants (61 %) would agree to fill in an online form daily, while 39.5 % would agree to use wearable devices for few hours, 36 % would agree to receive push notification that block their screen, and only 11 % would give access to data from their smartphone GPS tracking.

7. Discussion

7.1. Factors associated with WTS

The Mixed Logit Model and additional questions give first insights into associations between key preferences of the participants regarding data sharing and WTS.

Regarding the **type of data** collected (PRQ1), the collection of **demographic** data had a weak association with WTS consistently across all country samples. Collection of **physical data** also had weak association with WTS, with some heterogeneity in the US sample. This observation is interesting for researchers, as ethical boards – as discussed by [45] and in the authors' experience – often view the collection of metrics such as age or physical data at workplaces as critical. At the same time, authors acknowledge that ethical boards and data protection officers have the task to protect participants based on objective risks, rather than participants' preferences or perceived risks. The overall indifference in the Polish sample, with only physiological data excluded from a positive attitude, and its homogeneity could reflect the greater demographic homogeneity observed in this sub-sample with regards to important demographics: three quarter of the participants in the Polish sample are in the age group 30–49, and around 80 % hold a post-graduate degree, distinguishing this from the other samples. Additionally, the sample size from Poland is smaller, which could decrease its representativeness. The German sample shows, in general, a higher sensitivity in using several types of data, whereas homogeneity together with indifference was only found for demographics and physical data. This finding is consistent with our expectations, as Germany's implementation of the GDPR regulations is rather strict and changes to everyday procedures may have increased public awareness of its implications, making a broad proportion of the population more familiar with the potential consequences of data sharing [46].

According to our results, **Activity Monitoring** (mentioned by [47]) and **Physiological data** have a negative association with WTS in two out of three country samples. For **Psychological data** this is true for one country sample. One could argue that this outcome corresponds with the notion that sharing knowledge about physical data is perceived as having fewer consequences compared to sharing **activity, psychological or even physiological data**.

How important were those data types for choice card scenario selection as directly weighted by the participants in the additional questions? Consistently with the above-described findings, demographics ranked the least important out of 5 possible ranks and physical data was less influential. Psychological data, and activity data were ranked most important though with differences between the country samples. Physiological data sharing was ranked moderately.

For **data acquisition strategies of researchers**, demographic information is potentially seen by people less critical to be collected, and physical data seem also to find a broad acceptance.

Overall, the data demonstrated differences between individual country samples and partly within sample heterogeneity, which may suggest that cross-cultural differences as well as diverging opinions in the countries co-exist. We cannot evaluate whether one or the other would be dominating based on our data, due to possible data collection bias because of the data collection strategy: the samples' composition was diverging between the countries as discussed later in the section on methodological limitations.

For **responsible organisation for data collection and use**, universities or research institutions had a positive association with WTS over government departments as known from literature [17]. For-profit organisations had a strong negative association with WTS in all country samples. All country samples except the US indicated no difference between government department and a not-for-profit organisation, placing them as the second preferred option. The US respondents, instead, seem to regard not-for-profit organisations in the same way as university/research institutions, indicating participants would be more

WTS data with those organisations compared to government departments.

What could be possible reasons for the difference between government departments and not-for profit organisations seen in the US sample? In the US, not-for-profit organisations have potentially a different status compared to Germany or Poland. Not-for-profit organisations often stand for tasks which are taken over by the government in Europe. Not-for-profit organisations could also be connected to a charity activity level which may be more highly regarded in the US compared to the other country samples. Another possible explanation is that the pattern may reflect comparatively lower levels of trust in governmental organisations in the US, possibly linked to broader cultural tendencies, the role of the state, or a recent decline in institutional trust. With respect to the last point, there are varying levels of trust to governments depicted in surveys globally. A cross-national survey [48] that includes participants from 30 countries (not including Poland or the US) shows a 39 % attitude of high or moderately high trust to governments on average, but with a gap of more than 43 percentage points across the sample. For the US the data available suggests a low level of trust to the federal government (in relation to the OECD range), between 22 % [49] and 40 % [50] for doing "what is right". Data from the US however also suggests a steady public support in terms of trust to the non-profit sector, including charities [51].

Participants indicated a preference for **anonymity;** many reported greater WTS their information when anonymity was guaranteed. The German and US sample suggest that there may be subgroups within the country samples with varying attitudes — some respondents may strongly prefer more anonymity, while others may prefer less in those locations. In contrast, for Poland, there is homogeneity in the preference for total anonymity. This observation indicates that the Polish participant group shows a higher agreement regarding restriction to anonymity than other country samples, which again could be explained by the sample characteristics, smaller sample size or other non-observed factors.

Autonomy also had a strong positive association with WTS, as respondents strongly rejected the option~~s~~ where they had "no control" over their data. For the German and the Polish participants, the categories to "view the data" or to "view and delete your own data" or to "view, delete, and choose what and how often your data can be collected" seemed to offer similar control level. Also, in both the German and the Polish sample, there was agreement about this evaluation. Not so for the US sample, who distinguished sharply between being able to change the data collected from them (represented by the two options containing "delete") and not having this opportunity in the variants with "no control" or "viewing the data". However, in the US, differing opinions seem to exist as we found heterogeneity in the answers.

One explanation for these results could be that participants, as in the German or Polish sample, may associate their WTS data with a belief that the data will be handled in compliance with GDPR regulations; if such compliance was not assumed, they might be less inclined to take part in the study. Another explanation could be that the Polish and the German sample would be aware that they can at any time withdraw their participation when their identity is known [52,53]. However, they might also think otherwise, not believing that changing of data is realistic (e.g., nobody would take time for this, or it would be too complicated regarding administrative processes). It is possible that they are just aware that it would not be meaningful or may create challenges for the data collector to change datasets after they have given their consent. However, we have not collected any information which would support a tendency for one or the other explanation.

In the literature, personal control regarding personal data protection is known as one of the most important drivers for the WTS personal data [16]. Insofar, our results on personal control represented by the parameters level of anonymity and autonomy underline such importance. The importance of drivers related to data control for scenario choice revealed that the level of anonymity ranks first followed by the level of autonomy – though not consistent across the country samples. Who collects and uses the data primarily is ranked third and secondary use of data ranks last in this comparison. These results align with the MXL model's finding that no control over data was associated with a lower WTS data.

For **secondary use of the data**, there was a weak association between WTS information and purposes such as market research across all samples. Thereby, we found heterogeneity in answers in the German and US sample, whereas homogeneity was observed in the Polish sample that was indifferent towards market research use. Using the collected data also for university research was consistently seen as indifferent in the US and German sample, while the Polish respondents demonstrated a consistently strong association between WTS data with secondary use of data for university research. The homogeneity observed in the Polish sample – both regarding preference for university research as additional use and for preference for university management over Government and not-for-profit organization management – is potentially related again to the demographics of this sample. The large representation (~80 %) of postgraduate degree holders in this country sample suggests a more homogenous level of familiarity with academic data use, research ethics and governance. Using the data also for governance and policy making was seen indifferent in the German and Polish sample while the US samples expressed a negative attitude towards this type of data use. While the Polish sample again showed homogeneity, the heterogeneity in the US and German sample gives reason to assume that there are subgroups with differing opinions. The negative attitude towards governance and policy making use in the US sample is consistent with the above-mentioned hypothesis of a lower trust in (federal) governmental institutions in the US.

Miesler and Bearth [16] mention the "Big Data Paradox" after which people in general are reserved to share their data but act otherwise in certain situations [54,55]. Therefore, the analysis of **conditions for sharing** was part of our study. Knowledge of what, where and why data are shared, energy reduction or other benefits for the company, and improvements of the indoor environmental quality at the workplaces were identified as relevant conditions associated with scenario choice. Most important across all country samples were comprehensive information on data use and the personal benefit from the data sharing. However, though studies found that one fifth to one quarter of people are willing to share personal health data, factors such as age, education level and occupation of study participants, and the level of digitalisation in the respondents' countries were found to be associated with the WTS data [17]. For instance, our results suggest that differences in the digitalisation status of the three countries Germany, Poland [56] and the US [57] exist. Though we collected this information, the analysis of such possible association in our data remains to be investigated.

Regarding an acceptable **frequency of collection**, the WTS decreases with increasing frequency. This observation was also reported in a thermal comfort longitudinal survey [58]. However, reported acceptable frequencies varied by data-collection method; in this sample, less intrusive methods co-occurred with higher reported acceptable frequencies. As there is often a relation between intrusiveness and the type of data collected, we see a similar tendency as in the type of data analysis: demographics – typically with a questionnaire, collected once- and physical data – typically measured close to the workspace but not at the person, continuously collected- are data types and collection methods which are likely to find good acceptance. On the other hand, GPS tracker, wearable devices or push notifications are more intrusive as they either survey continuously or force reactions at unexpected points of time. At the same time, they collect information which is regarded as being more sensible for occupants: activity data and physiological data.

7.2. Methodological limitations

We chose the choice card approach to be able to investigate the association between the importance of several factors and WTS and to evaluate the relation of the factors to each other. In this regard, the choice card approach succeeded to answer our general research question. However, feedback from a few participants revealed that some experienced difficulties maintaining concentration when comparing the different scenarios presented to them in the choice cards. It was necessary to collect a large number of surveys, as respondents faced challenges in interpreting choice card attributes or in paying proper attentiveness to the given answers. After considering all criteria and evaluating response patterns, a sample of 34.5 % of the collected surveys remained adequate to evaluate the results. To reach a higher percentage of participants completing the whole survey and with the knowledge of this study, the results of our study offer opportunities to reduce the complexity of the choice cards. In addition, due to the lack of existing and validated choice cards and questionnaires, the authors had to develop their own versions. While the choice cards had been critically tested beforehand [31], there had been no validation of the additional questions. Besides the acceptable consistency of these items (Cronbach's alpha = 0.71), further validation is necessary.

Our analysis showed differences in the WTS between the country samples. Those differences could have several reasons.

Firstly, they could be rooted in factors related to the composition of our samples (Table 2) which shows for example an unbalanced distribution for gender, level of education (Poland) and age classes across the samples. Table 3 revealed, that in the US and the German sample heterogeneity of opinion was observed for many parameters contrary to the homogeneity observed in the Polish sample. This result could be attributed to the smaller sample size achieved in the latter, or in a generally homogeneous participants sample due to the different recruiting strategy. For the Polish sample, the recruiting strategy was mainly through institutional channels and therefore, it must be considered as a convenience sample with all related limitations. For instance, it is not surprising that there are more academics included with possible impact on the resulting preferences.

Secondly, other non-observed factors, such as prior knowledge and interest on data management and data protection and respective differences in them between country samples, might have moderated some of the study outcomes.

Thirdly, the German and the US sample were paid whereas the Polish and the participants from the other countries were not paid. This is another reason we are not in the position to make causal reasoning for possible influencing factors on differences between the countries.

Fourthly, some of the data is expected to display influences relating to potential ambiguities caused by wording choices made in setting up the survey. The cognitive testing [31] conducted with UK participants prior to the roll out of the main survey provided some insights, with participants found to over-interpret some of the wording and requiring more precise descriptions for the responsible for data collection organisations and use. The revisions made following the cognitive testing seem to have addressed these limitations in some, but not all the contexts included. For the US context, a study by [51] points to the fact that universities in the US are primarily non-profit and that respondents to surveys often show uncertainty in what "non-profit" means. Correspondingly, in observing the results from the complete data, one could potentially interpret the overall alignment against for-profit organisations as being also related to the lack of ambiguity in the term itself, whereas the boundaries between terms such as university, research and non-profit may be unclear in some contexts, and thus contribute to the lack of a unified preference for management of data by such organisations. In relation to observed attitudes towards for-profit organisations and market research, some useful insights are again offered in the evidence gathered during the cognitive testing [31], pointing primarily to concerns relating to underlying motives and practices relating to data security. To which extent these views represent the attitudes seen in the country samples and overall sample discussed here is however not possible to capture, as such pretesting was not conducted with participants from the other locations surveyed.

All the points mentioned above also form the limitations of this study. However, the strength of this study can be seen in concrete scenarios presented, forming a concrete background for the participants' choices and preferences. This study focused on identifying the enablers and barriers of including aspects and methods for data collection to facilitate research and environmental control of spaces to improve comfort and energy consumption. Therefore, the underlying reasons behind participants' choices was limited and could be further explored, for example, by applying validated questionnaires addressing trust and privacy [59,60] in the work environment.

8. Conclusion

This paper presents a first investigation into office workers' willingness to share (WTS) information that could be used for improving their comfort level and the energy efficiency of their buildings. As such, this work is at the critical intersection between privacy concerns and the growing demand for innovative technological solutions in the built environment.

Through a stated preference discrete choice experiment tailored to the area of built environment research in which participants had to choose between scenarios developed by the authors, the study explored associations between occupants' WTS data and the types of information to share, and how important it is to them who collects and manages the information they provided. The experiment was conducted in selected countries across five continents, providing insights into potential regional or cultural differences in data-sharing preferences.

The results of the analysis suggest the following insights into the research questions given the limitations of the sample:

- PRQ1: association with data type. While respondents displayed relative indifference to sharing demographic and physical environmental data, they showed more concern about psychological and activity-related data. Demographic data is given both the least weight and overall indifference to the provision of this information. Collecting physical parameters in an office room is user-indifferent and furthermore, this attribute has less influence on the overall weight of the decision for information sharing. Variations in acceptance levels across country samples were observed, with differences in age, education level, occupation, cultural or other factors.
- PRQ2: association with context of the collection. The findings suggest that protection of identity and personal data is paramount. It underscores the universal prioritization of total anonymity and data autonomy, highlighting a strong emphasis on privacy and individual control. Participants' WTS data was positively associated with the collection managed by neutral or academic institutions, with consistent negative associations with collection by for-profit organizations. At the same time, the differences in the WTS information between country samples emphasize the importance of tailoring data-sharing strategies to specific regional and cultural contexts. Transparency and minimum degree of control (autonomy) was requested as fundamental conditions for participants' WTS data. However, the level of requested control differed and had various ranges between country samples.
- SRQ1: association with benefits. Direct personal benefits, such as improved workplace environmental conditions, appear more strongly associated with an increased WTS data than indirect benefits, such as reduced energy costs for employers. This trend reflects the relative weight of direct benefits in participants' data-sharing preferences.
- SRQ2: association with collection frequency. Participants generally preferred infrequent data collection, with a majority expressing a preference for a one-time or monthly data-sharing frequency. Acceptance declined as the frequency increased, particularly for daily or continuous monitoring. One hypothesis is that combining higher frequencies with transparent, personal control over data-

sharing, and less intrusive methods could be associated with higher acceptability; this was not assessed in the present data.
- SRQ3: association with collection method. Survey responses indicate a preference for non-intrusive data collection methods such as online forms, while more invasive technologies, including wearable devices and smartphone GPS tracking, were met with resistance. Passive data collection via environmental sensors was generally more acceptable if anonymity and user control were ensured.

Participants' sensibility to the surveyed data types, collection purposes and frequency suggest strengths and weaknesses of data sharing for thermal comfort and energy efficiency at the workplace. On the one hand, collecting demographic and physical data (the most user-indifferent and probably easiest to share) related to thermal, lighting and acoustic environments is crucial to many survey approaches, such as feeding thermal comfort predictive models and energy consumption estimations. On the other hand, participants' restrictions regarding sharing psychological and activity data are concerning, particularly under a higher frequency of data collection – often used e.g. in comfort field surveys conducted in real settings. Additionally, the benefits of thermal comfort and energy efficiency are likely perceived differently, since the former is direct and personal, while the latter is indirect in typical office settings. The outcomes of this study highlight attributes valued by participants in data sharing, such as direct perceived benefits, full anonymity and diminished frequency of collection.

Overall, the results highlight the need to balance the progress of successful energy efficiency and thermal comfort initiatives requiring the alignment of technical solutions based on shared data with nuanced societal needs and with respect for individual rights. Moreover, this research provides valuable contributions to understanding data-sharing behaviours in the built environment, offering practical recommendations for and effective practices in gathering personal data in the context of indoor environment and energy efficiency. The findings of our project indicate good agreement with the information described in the literature.

While the applied method is a powerful tool, its complexity due to the number of scenarios and choice cards has required participants to devote significant time and concentration. This and further limitations with respect to the sample size and composition do not permit generalizing results as discussed in the main part. In the future, it is important to be aware of the need to limit the number of options to the smallest possible, as well as to obtain a larger representative sample for the country or target group of interest.

In addition, results suggest differences in the WTS data between individuals and larger groups, so that future research should further explore cultural, ethical, and legal dimensions of data sharing among others, fostering interdisciplinary collaboration to advance sustainable and responsible innovations in building operations. Future studies should also deepen the understanding of the motivation to share information related to trust and need for privacy in the work environment.

CRediT authorship contribution statement

Marcel Schweiker: Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Dimitris Potoglou:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Farah AlAtrash:** Writing – review & editing, Investigation, Conceptualization. **Eleni Ampatzi:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Funding acquisition, Conceptualization. **Maíra André:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis. **Elie Azar:** Writing – review & editing, Writing – original draft, Investigation. **Karol Bandurski:** Writing – review & editing, Writing – original draft, Investigation. **Leonidas Bourikas:** Writing – review & editing, Methodology, Investigation. **Carolina Buonocore:** Writing – review & editing, Writing – original draft, Investigation, Formal analysis. **Bin Cao:** Writing – review & editing, Writing – original draft, Investigation. **Giorgia Chinazzo:** Writing – review & editing, Writing – original draft, Investigation. **Rania Christoforou:** Writing – review & editing, Writing – original draft, Investigation. **Sarah Crosby:** Writing – review & editing, Writing – original draft, Investigation. **Renata De Vecchi:** Writing – review & editing, Writing – original draft, Investigation. **Edyta Dudkiewicz:** Writing – review & editing, Writing – original draft, Investigation. **Ricardo Forgiarini Rupp:** Writing – review & editing, Writing – original draft, Investigation. **Stephanie Gauthier:** Writing – review & editing, Methodology, Investigation, Conceptualization. **Natalia Giraldo Vasquez:** Writing – review & editing, Writing – original draft, Investigation. **Runa T. Hellwig:** Writing – review & editing, Writing – original draft, Methodology, Investigation. **Gesche M. Huebner:** Writing – review & editing, Methodology, Conceptualization. **Marta Laska:** Writing – review & editing, Writing – original draft, Investigation. **Marín-Restrepo Laura:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation. **Isabel Mino-Rodriguez:** Writing – review & editing, Methodology, Formal analysis, Conceptualization. **Mohamed M. Ouf:** Writing – review & editing, Writing – original draft, Conceptualization. **Romina Rissetto:** Writing – review & editing, Writing – original draft, Formal analysis, Data curation. **Philip Turner:** Writing – review & editing, Methodology, Investigation, Conceptualization. **Yijia Wang:** Writing – review & editing, Writing – original draft, Investigation.

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.

Acknowledgements and funding information

M.S. and R.C. were funded by a research grant (21055) by VILLUM FONDEN. C.B. was funded by a research grant (001) by the Coordination for the Development of Higher Education Personnel – Brazil (CAPES). E. Am. received funding from the Welsh School of Architecture for the execution and reporting of the cognitive interviews. E.Az. was funded by the Canada Research Chairs Program (CRC-2021-00235). K.B. was funded by Poznan University of Technology (0713 SBAD 0980 MK). M. O. was funded by the NOVA-FRQNT-NSERC Program for Junior Researchers (#344877) The contribution of S.G. and P.T. were supported by the EPSRC Grant EP/T023074/1 "LATENT: Residential Heat As An Energy System Service". L.M.R was funded by the Belgian National Fund for Scientific Research (F.R.S.-FNRS), project CR 40005384. R.T.H. was supported by the Obelske Familiefond.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.buildenv.2025.113918.

Data availability

The manuscript includes a link to the data storage on osf.io.

References

[1] J. Pryce-Jones, Happiness at work: maximizing your psychological capital for success, in: Happiness At work: Maximizing your Psychological Capital For Success, xii, Wiley Blackwell, Hoboken, NJ, US, 2010, p. 241.
[2] T. Harputlugil, P. de Wilde, The interaction between humans and buildings for energy efficiency: a critical review, Energy Res. Soc. Sci. 71 (2021) 101828.
[3] M. Schweiker, et al., Review of multi-domain approaches to indoor environmental perception and behaviour, Build. Environ. (2020) 106804. -106804.

[4] Y. Zhao, D. Li, Multi-domain indoor environmental quality in buildings: a review of their interaction and combined effects on occupant satisfaction, Build. Environ. 228 (2023) 109844.
[5] A. Buonomano, et al., Enhancing energy efficiency and comfort with a multi-domain approach: development of a novel human thermoregulatory model for occupant-centric control, Energy Build. 303 (2024) 113771.
[6] B. Qolomany, et al., Leveraging machine learning and big data for smart buildings: a comprehensive survey, IEEE Access 7 (2019) 90316–90356.
[7] N. Gao, et al., Understanding occupants' behaviour, engagement, emotion, and comfort indoors with heterogeneous sensors and wearables, Sci. Data 9 (1) (2022) 261.
[8] P. Jayathissa, et al., Humans-as-a-sensor for buildings—Intensive longitudinal indoor comfort models, Buildings 10 (10) (2020) 174.
[9] S. Liu, et al., Personal thermal comfort models with wearable sensors, Build. Environ. 162 (2019) 106281. -106281.
[10] S. Altomonte, et al., Ten questions concerning well-being in the built environment, Build. Environ. 180 (2020) 106949.
[11] F. Tartarini, et al., Personal comfort models based on a 6-month experiment using environmental parameters and data from wearables, Indoor Air 32 (11) (2022) e13160.
[12] Y. Xu, D. Wang, Understanding the willingness to share building data by a social study based on privacy calculus theory, in: Proceedings of the 9th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation, Association for Computing Machinery, 2022, pp. 59–68, numpages = 10.
[13] S. Schudy, V. Utikal, You must not know about me'—On the willingness to share personal data, J. Econ. Behav. Organ. 141 (2017) 1–13.
[14] P.A. Pavlou, State of the information privacy literature: where are we now and where should we go? MIS Q. 35 (4) (2011) 977–988.
[15] H. Yun, G. Lee, D.J. Kim, A chronological review of empirical research on personal information privacy concerns: an analysis of contexts and research constructs, Inf. Manag. 56 (4) (2019) 570–601.
[16] L. Miesler, A. Bearth, "Willingness to share" im Kontext Big Data: Wie entscheiden Kunden, ob sie ihre persönlichen Daten mit Unternehmen teilen?. Dialogmarketing Perspektiven 2015/2016: Tagungsband 10. Wissenschaftlicher Interdisziplinärer Kongress für Dialogmarketing Springer Fachmedien Wiesbaden, Wiesbaden, 2016, pp. 49–66.
[17] M. Karampela, S. Ouhbi, M. Isomursu, Connected health user willingness to share personal health data: questionnaire study, J. Med. Internet Res. 21 (11) (2019) e14537.
[18] C. Maier, et al., Influencing factors on consumers' Willingness to share energy data on online energy platforms, Bus. Manag. Stud. 7 (2) (2021) 13–22.
[19] S. Yussof, et al., Willingness of electricity consumer in Malaysia to share electric energy consumption data. Advances in Visual Informatics, Springer International Publishing, Cham, 2021.
[20] J.A.L. Reyes, Willingness to share information for energy efficiency: exploring differences and drivers across the Nordic countries, Energy Sustain. Soc. 12 (1) (2022) 38.
[21] European Commission, Attitudes towards the impact of digitalisation on daily lives. Digitalisation in Our Daily Lives, 2020.
[22] B. Li, A. Tavakoli, A. Heydarian, Occupant privacy perception, awareness, and preferences in smart office environments, Sci. Rep. 13 (1) (2023) 4073.
[23] S. Harper, et al., User privacy concerns in commercial smart Buildings1, J. Comput. Secur. 30 (3) (2022) 465–497, numpages = 33.
[24] E.R. Weitzman, et al., Willingness to share personal health record data for care improvement and public health: a survey of experienced personal health record users, BMC Med. Inform. Decis. Mak. 12 (1) (2012) 39.
[25] C. de Terwangne, Council of Europe convention 108+: a modernised international treaty for the protection of personal data, Comput. Law Secur. Rev. 40 (2021) 105497.
[26] M.S. Righettini, Institutionalization, leadership, and regulative policy style: a France/Italy comparison of data protection authorities, J. Comp. Policy Anal.: Res. Pract. 13 (2) (2011) 143–164.
[27] Badillo, M. and M. Imran, Regulatory strategies and priorities of data protection authorities in Latin America: 2024 and beyond. 2024, Future of Privacy Forum.
[28] Y. Yousefi, Data sharing as a debiasing measure for AI systems in healthcare: new legal basis, in: Proceedings of the 15th International Conference on Theory and Practice of Electronic Governance, Association for Computing Machinery, 2022, pp. 50–58, numpages = 9.
[29] H.B. Bentzen, Exchange of Human data across international boundaries, Annu Rev. Biomed. Data Sci. 5 (2022) 233–250. Volume 5, 2022.
[30] D.A. Hensher, J.M. Rose, W.H. Greene, Applied Choice Analysis, 2 ed, Cambridge University Press, Cambridge, 2015.
[31] P. Haggar, et al., Information sharing preferences within buildings: benefits of cognitive interviewing for enhancing a discrete choice experiment, Energy Build. 258 (2022) 111786.
[32] H.J. Smith, T. Dinev, H. Xu, Information Privacy Research: An Interdisciplinary Review, 35, MIS Quarterly, 2011, pp. 989–1015.
[33] D. Potoglou, et al., Quantifying individuals' trade-offs between privacy, liberty and security: the case of rail travel in UK, Transp. Res. A: Policy Pract. 44 (3) (2010) 169–181.
[34] S. Patil, et al., Public preferences for electronic health data storage, access, and sharing - evidence from a pan-European survey, J. Am. Med. Inform. Assoc.: JAMIA 23 (6) (2016) 1096–1106.
[35] D. Potoglou, et al., Public preferences for internet surveillance, data retention and privacy enhancing services: evidence from a pan-European study, Comput. Hum. Behav. 75 (2017) 811–825.
[36] D. Potoglou, J.-F. Palacios, C. Feijóo, An integrated latent variable and choice model to explore the role of privacy concern on stated behavioural intentions in e-commerce, J. Choice Model. 17 (2015) 10–27.
[37] Schweiker, M., et al. A79-WTS: occupants willingness to share information for improved comfort and energy efficiency. 2021; Available from: https://doi.org/10.17605/OSF.IO/GZV7F.
[38] Choice metrics, Ngene 1.3. User Manual & Reference guide, 12.03.2025]; Available from, https://www.choice-metrics.com/NgeneManual130.pdf, 2025.
[39] E.W. de Bekker-Grob, M. Ryan, K. Gerard, Discrete choice experiments in health economics: a review of the literature, Health Econ. 21 (2) (2012) 145–172.
[40] J.M. Rose, M.C.J. Bliemer, Sample size requirements for stated choice experiments, Transportation (Amst) 40 (5) (2013) 1021–1041.
[41] D. McFadden, in: P. Zarembka (Ed.), Conditional Logit Analysis of Qualitative Choice Behavior, Academic Press, New York, 1973, pp. 105–142. Editor.
[42] M.E. Ben-Akiva, S.R. Lerman, Discrete Choice analysis: Theory and Application to Travel Demand, 9, MIT press, 1985.
[43] D. Revelt, K. Train, Mixed logit with repeated choices: households' choices of appliance efficiency level, Rev. Econ. Stat. 80 (4) (1998) 647–657.
[44] European Social Society, Education upgrade ESS1-ESS4. Documentation report. 2023.
[45] H. Nissenbaum, *Privacy in Context*. Technology, Policy, and the Integrity of Social Life, Stanford University Press, 2009.
[46] A.F. Westin, Social and political dimensions of privacy, J. Soc. Issues 59 (2) (2003) 431–453.
[47] D.J. Solove, A taxonomy of privacy, Univ. Pa. Law Rev. 154 (3) (2006) 477–564.
[48] OECD, OECD Survey on drivers of trust in public institutions –2024 results: building trust in a complex policy environment. 2024.
[49] Pew Research Center, Public Trust in Government: 1958-2024, 12.03.2025]; Available from, https://www.pewresearch.org/politics/2024/06/24/public-trust-in-government-1958-2024/, 2024.
[50] P. Hitlin, N. Shutava, Trust in government A close look at public perceptions of the federal government and its employee, 12.03.2025]; Available from, https://ourpublicservice.org/wp-content/uploads/2022/03/Trust-in-Government.pdf, 2022.
[51] M. O'Neill, Public confidence in charitable nonprofits, Nonprofit. Volunt. Sect. Q. 38 (2) (2009) 237–269.
[52] B. Dahal, Participants' Right to withdraw from research: researchers' Lived experiences on ethics of withdrawal, J. Acad. Ethics 22 (1) (2024) 191–209.
[53] E. Chwang, Against the inalienable right to withdraw from research, BioEthics 22 (7) (2008) 370–378.
[54] A. Acquisti, L.K. John, G. Loewenstein, What is privacy worth? J. Leg. Stud. 42 (2) (2013) 249–274.
[55] P.A. Norberg, D.R. Horne, D.A. Horne, The privacy paradox: personal information disclosure intentions versus behaviors, J. Consum. Aff. 41 (1) (2007) 100–126.
[56] European Commission, The digital economy and society index (DESI). 2024.
[57] Brunori, B., et al., Digitalisation in Europe 2022-2023: evidence from the EIB investment survey. 2023.
[58] F.Z. Al-Atrash, R.T. Hellwig, A. Wagner, Indoor environment in office buildings – Perception of personal control and use of adaptive opportunities at workplaces, Bauphysik 44 (5) (2022) 264–281.
[59] S.S. Tzafrir, S.L. Dolan, Trust me: a scale for measuring manager-employee Trust, Manag. Res.: J. Iberoam. Acad. Manag. 2 (2) (2004) 115–132.
[60] R. Kramer, et al., The organizational trust inventory (OTI): development and validation. The Organizational Trust Inventory (OTI): Development and Validation, SAGE Publications, Inc, 1996, pp. 302–330.