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Article

The influence of individual and organizational factors on the energy efficiency of office buildings: A consolidation

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ABSTRACT

A significant portion of global energy demand is directly attributable to artificial lighting systems in buildings. Consequently, improving their energy efficiency is crucial for achieving current climate and environmental policy goals. However, the prevailing discrepancies between predicted and actual energy demand present a major challenge as a comprehensive understanding of the factors influencing energy consumption of artificial lighting systems is still lacking. Based on minute-by-minute long-term monitoring of an open-plan office in Austria several dedicated studies have been conducted in recent years to systematically and comprehensively quantify the impact of individual and organizational factors on energy consumption. In addition to quantifying workplace usage behaviour, the analyses also considered various control concepts and the influence of user combinations, both on an individual and probability-based level. The results emphasize the need for a greater integration of behavioural aspects into the strategic planning and operation of artificial lighting systems to optimize energy efficiency.

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INTRODUCTION

Despite numerous efforts to enhance energy efficiency, the building sector remains responsible for approximately 30% of greenhouse gas emissions and about 40% of global energy demand, with artificial lighting being a major energy consumer (Dubois & Blomsterberg, 2011). In recent years, both building-related modelling techniques and energy-efficient technologies have achieved significant improvements. Despite these advancements, buildings often fail to meet the energy targets anticipated during planning and simulation phases. Current studies (Liang et al., 2019; Calì et al., 2016) show that actual energy consumption can exceed estimates made during the planning phase by up to threefold. Additionally, the efficiency of implemented control systems is rarely evaluated after they have been put into operation, leading to substantial challenges in meeting energy and environmental policy objectives. To improve the energy efficiency of lighting systems and reduce the risk of incorrect design estimates of energy demand, a

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deeper understanding of the causes of energy performance gaps (EPGs) (Cozza et al., 2021) and a comprehensive quantification of their magnitude is needed to both improve the accuracy of building performance design and simulation and ensure a positive contribution to societal challenges.

As a result, numerous studies on this topic have been conducted to date (Zou et al., 2019; De Wilde, 2014; Menezes et al., 2012). These studies reveal that the existing discrepancy between actual energy consumption and simulated forecasts, as described by the EPG, is closely linked to concepts of optimal energy usage. Therefore, they not only relate to the optimal functioning of a building, focusing on structural and design factors, but also to ensuring user-related requirements are met (Cozza et al., 2021). Estimating building energy consumption is therefore highly complex, and deviations during actual operation often result from the interaction of multiple factors (De Wilde, 2014).

Potential influences on deviations in operational energy consumption range from insufficient fine-tuning of control systems and suboptimal settings of technical components (Zou et al., 2019) to inaccuracies in measurement techniques and uncertainties in building modelling specifications (Calì et al., 2016). Unrealistic assumptions and forecasting errors in climate data (Erba et al., 2017) and occupancy models during the planning phase (De Wilde, 2014) further contribute to the manifestation of EPGs. System errors or improper use of systems by building occupants (Cozza et al., 2021; Menezes et al., 2012) can also have a significant impact. It is important to understand that it is almost impossible for building users to assess the energy impacts of system interventions, as they lack appropriate quantification mechanisms. As a result, decisions are primarily based on the satisfaction of immediate personal needs (Barthelmes et al., 2016), which may not necessarily align with long-term strategic and energy-saving control concepts. Consequently, it is currently assumed that uncertainty in user behaviour significantly influences the accuracy of energy demand performance forecasts made during the planning phase (Yoshino et al., 2017).

From a planning perspective, this critical role of user behaviour in contributing to the performance gap arises from a lack of detailed information about organizational and socio-cultural factors during the planning phase. The assumptions about occupancy behaviour used in planning and simulation are primarily based on empirically validated and standardized models, which are formulated as broadly as possible to ensure wide applicability (Wang et al., 2016). However, workplace occupancy dynamics are significantly influenced by individual factors such as job tasks, professional position within the organization, and social conditions, all of which can vary considerably between organizations and individuals. Consequently, the energy impacts of occupancy profiles are often stochastic (Zhou et al., 2015) and do not correspond to the static occupancy models used today. The issues arising from current model assumptions become evident in contexts with flexible social structures, such as flex-time regulations and remote work. Furthermore, workplace-specific dynamics, such as the proportion of meetings depending on the job position in an organisation (Panko & Kinney, 1995), present a practical challenge insufficiently addressed by current assumptions.

Currently, several approaches exist to address these problems in building energy simulations. For example, discrete Markov processes, based on predictors selected for statistical significance through forward and backward selection (Haldi et al., 2017), offer the advantage of capturing individual behaviour on a statistical basis. In recent years, machine learning techniques have also been increasingly used (Yılmaz et al., 2023; Weninger & Hammes, 2024). The development of improved methods for modelling user behaviour and their integration into simulation environments has been the subject of both past and current research efforts within the framework of the “Energy in Buildings and Communities” program of the International Energy Agency (IEA EBC; Yoshino et al., 2017). However, a comprehensive and suitable quantification of the multidimensional factors influencing energy demand and contributing to the performance gap is still lacking. Thus, the quantification of EPG and the development of appropriate counterstrategies remain key research topics to avoid inefficient building operation and ensure the achievement of energy targets.

Scope of this Work

In 2019, a Living Lab was established in the open-plan office of the R&D department of Bartenbach GmbH in Aldrans, Austria. Since then, high-resolution user and building-related data have been collected as part of a post-occupancy evaluation. In comparison with simulation models, these data have been used in multiple studies to evaluate the building's energy consumption. In addition to the goal of thoroughly breaking down and weighting the factors influencing energy consumption, targeted approaches were pursued to mitigate existing performance issues. Due to the significant impact of occupancy behaviour on the success or failure of predictions made during the planning phase regarding the building's energy efficiency, the analyses focused primarily on individual and organizational influences and their relationship to other relevant factors such as daylight availability, season, time of day, and building usage.

Using statistical methods, machine learning, and mathematical optimization techniques, the available data were analysed both using real datasets and synthetic datasets generated through sampling methods. In addition to quantifying workplace usage behaviour, the analyses also considered various control concepts and the influence of user combinations, both on an individual and probability-based level. The findings underscore the need for increased integration of behavioural aspects into the strategic planning and operation of artificial lighting systems to optimize energy efficiency. Consolidated results from individual studies are presented, and future research perspectives are derived.

DESCRIPTION OF THE STUDY OBJECT

The research and development building of Bartenbach GmbH in Aldrans, Austria, features a 160 m² open-plan office accommodating up to 28 workstations. To ensure optimal operation and comfort, the office is primarily used by 18 individuals, distributed across nine workstation zones. Four zones, each designed for two people, are located along the north side under a skylight, while five additional zones, also standard for two but expandable to four people, are situated along the south facade (Figure 1, left).

Both the daylight and artificial lighting systems in the office space have been optimized over several years. As a result, the lighting systems in the study object can be controlled separately for each workstation zone to accommodate individual lighting preferences (Boyce et al., 2000; Despenic et al., 2017; Veitch & Newsham, 2000), avoid associated conflicts (Chraibi et al., 2016), and significantly reduce the system's overall energy consumption (Hammes et al., 2020). The artificial lighting system provides two colour temperatures, ranging from 5,000 K in the morning to 2,200 K in the evening, to support the users' circadian rhythms. It is controlled by ceiling-mounted passive infrared sensors (PIR; Thermokon, RDI) that respond to occupancy. The implemented switch-off delays have been adjusted to an industry standard of 15 minutes (Nagy et al., 2016) to prevent incorrect system shutdowns. Additionally, the necessary artificial lighting is reduced by desk-mounted horizontal light sensors (Thermokon, LDF 1000A) based on the available amount of daylight. In this context, a normative standard of 500 lx according to EN 12464-1 is assumed as the target value.

The office is characterized by a large, glazed area on the south facade, ensuring high levels of daylight integration. On average, horizontal illuminance levels of over 500 lx are achieved at workstations between 9:00 AM and 4:00 PM, resulting in a daylight autonomy (DA) of 81.56% (Figure 2). To prevent glare and overheating, automatically controlled shading systems are installed on the exterior of the south facade and the interior of the northern skylights, along with an external static daylight system (Figure 1, right), adapted to the specific conditions and geographic location of the building. The automated control logic for both artificial and daylight can be overridden by users within each workstation zone via switches, ensuring high user acceptance (Despenic et al., 2017).

The occupancy structure in the building is highly dynamic. Core working hours are from Monday to Thursday, 9:00 AM to 12:00 PM and 2:00 PM to 5:00 PM, and Friday from 9:00 AM to 12:00 PM. Additionally, the organizational framework includes the option for remote work and flexible hours between 6:00 AM and 8:00 PM. To capture individual occupancy behaviour, PIR sensors (NodOn, PIR 2 1 01) are installed under each workstation, with detection areas limited to the specific desk. The building is centrally controlled by a programmable logic controller (PLC, BECKHOFF, CX5140-0141), which also logs all sensor data and actuator system states. With over 100 sensors in the R&D building, comprehensive monitoring of the indoor and outdoor climate, as well as the presence and absence of users at their workstations, is ensured in compliance with data protection regulations.

Figure 1. Interior (left) and exterior view (right) of the Bartenbach R&D building in Aldrans, Austria. In the right part of the interior area, the skylights of the north façade can be seen, the exterior view shows the static daylight system on the south façade.

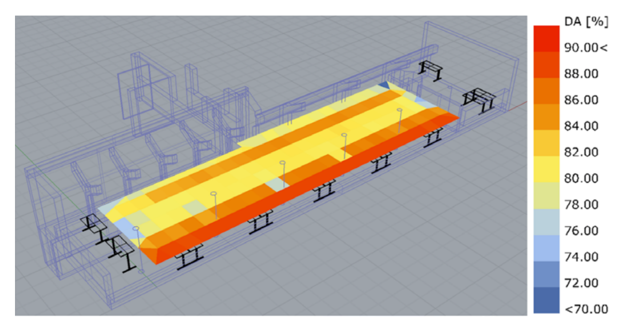

Figure 2. Daylight simulation of the study object, implemented with Radiance; simulation related to the normative minimum illuminance of 500 lx according to EN 12464-1; reference time: 8:00-18:00, daylight savings time not considered, calculated with glare protection.

Since 2019, all sensor data in the building have been collected in high resolution and stored in a machine-readable data format (.csv). Continuous data, such as those from lighting and environmental quality sensors, are recorded every minute. Status-based data, such as workstation occupancy or window opening states, are recorded on an individual level upon status changes. The collected data has been partially made available for research purposes (Hammes & Weninger, 2023).

STUDY RESULTS

Simulated and Real Energy Consumption

In general, energy consumption always results from a causal relationship, which arises from various influencing factors and their implementation in control systems. The extent to which this interdependence affects the results energy consumption simulations, especially in relation to the used occupancy model, was examined in a study conducted in 2021 (Hammes et al., 2021a). In this study, the building's energy consumption from September 2020 to October 2020 was simulated under several different control methods for the daylighting system, which included various assumptions about glare assessment and the corresponding limitation of available daylight indoors. Additionally, both static and dynamic occupancy models were simulated and compared to actual energy consumption data. To validate the accuracy of the simulations, a comparative energy consumption simulation was also conducted using actual measured workplace occupancy data.

The results showed a generally strong alignment with actual energy consumption, with an underestimation of approximately 14% due to hourly resolution of the weather data, in comparison to the real consumption of 121 kWh when using actual occupancy data in the simulation. Although this study found that both the assumed control method and the occupancy model had a significant impact on the simulated

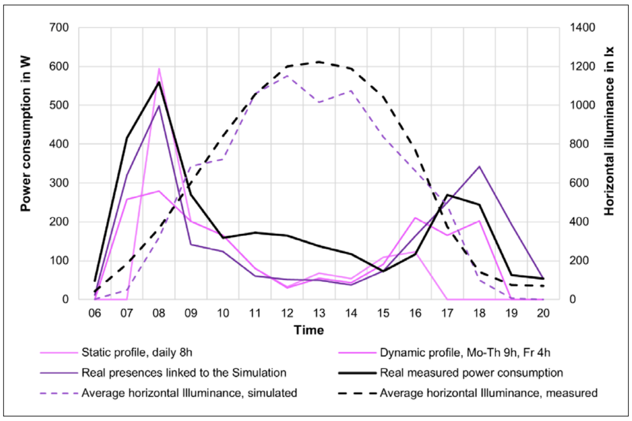

Figure 3. Average energy demand of different occupancy models, supplemented by the simulated and measured illuminance and the real energy demand (Hammes et al., 2021a).

energy consumption, the influence of the occupancy models was notably higher. Moreover, there was a considerable underestimation of the resulting energy consumption by approximately 50% on average. These discrepancies can largely be explained by the high availability of daylight, which, in many cases, shifts the primary use of artificial lighting to the early morning and late afternoon (Figure 3). In the building, due to the flexible working hours of employees, these times are characterized by high variability in occupancy, with considerable differences in the start and end times of the working day. Static occupancy models are inherently unable to capture these organizationally enabled variations, which manifest through individual behaviour. Adequately accounting for this variability in dynamic models also proves to be highly challenging. Although the dynamically assumed occupancy models in the study produced better simulation results, the deviations from actual energy consumption were still significantly underestimated.

Thus, assumptions regarding user behaviour in simulations must be considered primarily responsible for existing energy performance gaps. However, despite this insight, the study did not directly quantify the impact of user behaviour itself on the building's overall energy demand.

Influence of User Behaviour

In the context of integral, sensor-coupled control approaches, the energy demand for artificial lighting is determined, on the one hand, by the currently available amount of daylight, which is supplemented by artificial lighting to reach the normative minimum illumination level at the workplace, and on the other hand, by the utilization of the workplace. In most cases, the presence and absence of individual users must be considered in conjunction, as general lighting typically illuminates multiple workstations simultaneously. As a result, the energy efficiency of the overall system is directly influenced by the alignment of individual presence patterns (Figure 4).

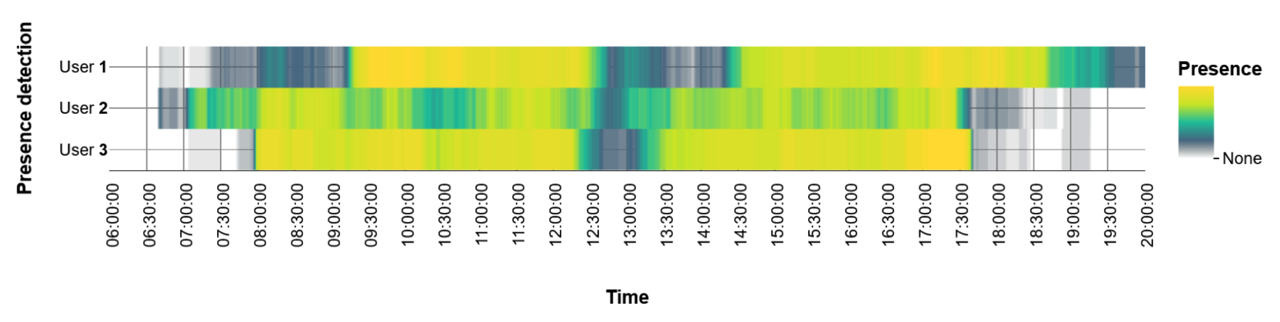

Figure 4. Exemplary representation of three real workplace occupancy profiles in the open-plan office, averaged daily in the period from September 2nd, 2020, to November 3rd, 2020 (yellow greenish: high occupancy, blue to grey: low occupancy, transparent: no occupancy).

In terms of fully quantifying the influence of individual user behaviour on the resulting energy consumption of a building, this circumstance presents a significant challenge, as substantial distortions can occur due to better or worse-suited user combinations, when only one specific room usage scenario is considered. Therefore, it is necessary to examine all possible combinations of users within a workplace zone and simultaneously account for their distribution across all available zones to obtain a comprehensive representation. However, even for smaller office spaces, such as the building studied with 18 users, this leads to more than 3 x 1029 possible spatial distributions of individuals. Consequently, this task cannot be solved within a finite amount of time. To nonetheless achieve a possible quantification of the influence of individual behaviour, a two-step optimization process using graph-theoretical algorithms was applied in a simulation-based study conducted in 2022 (Hammes et al., 2022). Real occupancy data for building users from July 2021 to November 2021 were paired for all combinations of two users, and the corresponding energy consumption was calculated using the zonally measured daylight availability. These data were then optimized for both user combinations and zonal assignment for best and worst-case scenarios.

The results show an increase in artificial lighting energy demand of approximately 83% from the best-case to the worst-case scenario (Table 1). For comparison, the actual energy consumption of the artificial lighting system during the nearly 100-day study period was around 83.8 kWh. Since the values were calculated using the same system configuration, the derived range only reflects user-related influences. The significant impact of individual behaviour on the overall energy demand of a building is not only confirmed by the present findings but also illustrates why current simulation assumptions, which would generally result in the same energy consumption for all scenarios due to the lack of individual variations, are insufficient for adequately estimating the performance indicators of real-world operations. To meet the requirements arising from this influence and to address the hidden potentials, the implementation of appropriate control strategies proves indispensable.

Effects of Using User-Centred Information

Given the nature of individual influences, the effects of users or user combinations are spatially highly zonal. To effectively address these effects, the implementation of finely zoned lighting concepts is necessary. However, compared to comprehensive room-wide lighting controls, such concepts require an increased use of sensors. This heightened system complexity also necessitates the use of more powerful control components, which can in turn have adverse effects on energy consumption. A direct comparison of differently zoned control systems was conducted in 2020 (Hammes et al., 2020). In a simulation-based study, the energy consumption of room-wide, as well as north- and south-facing, and individually

Table 1. Overview of the influence of user combination and room positioning on the energy consumption of the artificial lighting system in the open-plan office for the period from July 1, 2021, to November 19, 2021 (Hammes et al., 2022)

Occupancy Schemes	Adjustment of Room Position	
	Best-case scenario	**Worst-case scenario**
Adjustment of the user pairing		
Best-case scenario	58.4 kWh	88.2 kWh
Worst-case scenario	86.4 kWh	96.7 kWh

zoned control concepts was calculated. As additional benchmark value, energy consumption for a room-wide manual control scenario was considered in the study. The simulations were based on real data for occupancy and daylight availability from March 2021 to December 2021. The results clearly indicated the advantages of more fine-grained zoning, showing a reduction of approximately 55% in energy consumption compared to the sensor-based room-wide control approach (Table 2), highlighting the superior ability of smaller zones to respond to individual variations more effectively.

In addition, zoned lighting concepts offer further crucial advantages by allowing the integration of personalization methods through the connection of the lighting system to individual room areas. Beyond general comfort criteria, such as adjusting individually preferred lighting conditions, these systems can also contribute to energy optimization at a higher level. For example, a study conducted in 2021 (Hammes et al., 2021b) developed a method that adjusts the otherwise generalized switch-off times for PIR-based presence-controlled artificial lighting after leaving the workspace based on individual occupancy patterns. The method employed probabilistic approaches to individualize the switch-off times based on past information regarding the duration of absence from the workplace. The artificial lighting was turned off as soon as the probability of a longer absence exceeded the probability of a prompt return. This procedure was implemented within the control system of the open-plan office and evaluated under real usage conditions during the period from September 2020 to October 2020. Despite the relatively short periods of artificial lighting use in the open-plan office due to the high availability of daylight, the implemented method reduced overall artificial lighting energy consumption by 17%. A concurrent user survey also revealed that individual lighting control had no negative effects on user acceptance.

DISCUSSION

The presented results clearly demonstrate that the expected energy consumption of buildings is significantly shaped by the individual behaviour of their occupants. This fact currently poses substantial challenges for the planning and simulation process, as the existing variability cannot be adequately accounted for in the related estimates due to generalized model assumptions. As a result, not only do significant deviations from the predicted energy consumption arise, but there is also a risk of incorrect system sizing, flawed specification of requirements, or ineffective definitions of control strategies.

Although it is currently very difficult to estimate the real impact of individual behaviour in planning processes, even low-threshold considerations of the potential variability of building users have proven to be highly beneficial. Zonal, sensor-controlled lighting designs are often effective approaches to significantly mitigate uncertainties in planning processes. Moreover, these concepts offer expanded possibilities, enabling the broader utilization of energy-saving potentials through personalized control strategies.

In theory, a targeted use of personalized lighting concepts can also be used to promote non-visual light effects. In typical general lighting setups, non-visual effects are usually achieved through continuous exposure to specific lighting settings, as individual factors are not adequately represented in the lighting concept. However, there is emerging evidence that intermittent light interventions may also produce acute light effects (Chang et al., 2012; Weninger et al., 2022; Canazei et al., 2023), by showing not only improved cognitive performance but also reduced heart rate variability. These interventions not only potentially possess a greater effectiveness compared to continuous interventions (Güler et al., 2008), but they could also have energy-saving effects in comparison to current health-promoting lighting solutions, as they are based on a significant reduction in the periods during which high vertical illuminance is required.

Limitations

Even though the consolidated study results clearly indicate the significant influence of individual user behaviour on the building's energy consumption, they nevertheless constitute a case study. Personal influences on energy consumption are fundamentally tied to individual behaviour. Different building users, varying usage scenarios, or alternative organizational uses of the building may therefore lead to different outcomes. While the study results generally provide similar indicators, it must be assumed that further case studies with different usage patterns are required to make a universally valid statement.

Table 2. Simulation-based, normalized energy consumption of the artificial lighting system in the open-plan office according to differently zoned control concepts (Hammes et al., 2020)

	Room-wide controls, manual	Room-wide controls, sensor	North/South zoning, sensor	9 workplace zones, sensor
Normalized energy consumption	117%	100%	88%	45%

Additionally, it should be noted that the evaluated building is characterized by above-average daylight availability. As a result, large parts of the day do not require the use of artificial light in terms of normative requirements, which leads to greater variability in energy consumption at the edges of the day. Given that there is typically a higher fluctuation in occupancy times during these periods, it is potentially possible that the influence of occupancy behaviour is overestimated in the presented results. However, whether this overestimation exists, and to what extent it manifests, would require comparative studies, which are currently unavailable.

CONCLUSION AND FUTURE RESEARCH DIRECTIONS

Considering current climate and environmental policy discussions, improving the energy efficiency of buildings has become crucial for achieving increasingly important societal objectives. The lighting sector, as one of the largest electrical consumers in buildings, can make significant contributions. However, the realization of these potentials is currently hindered by inaccuracies in both the planning process and energy simulations as well as inefficient control strategies. User behaviour, which is influenced by both individual factors and organizational and social conditions, can therefore be considered as a central factor, as its impact on both the planning processes and the operation of controlled artificial lighting systems proves to be essential.

Both in relation to the improvement of user models and the design of user-centred lighting control systems, there are currently a variety of approaches (see, for example, Hammes et al., 2024). Specifically, advanced approaches utilizing data-intensive modelling techniques, such as machine learning algorithms, are becoming increasingly important in this field. However, the availability of relevant data remains significantly limited, as data collection is complex, and post-occupancy evaluations of building performance are still rarely conducted, despite their potential to address existing opportunities effectively. The primary reasons for this are often the cost and resource intensity associated with adapting control systems during operation.

In the context of personalized lighting control systems, this issue could be significantly mitigated. The adequate integration of user information generally aims not only to account for interindividual differences in the design of personal environments but also to recognize intrinsically or extrinsically motivated behavioural changes at an intraindividual level and to adjust control decisions accordingly. As a result, costly adjustments of implemented control logics would become a thing of the past in a fully personalized system, as these systems would operate within a framework of continuous re-evaluation of current decision-making and automatically perform necessary adaptations. In this context, reinforcement learning methods currently hold significant future potential.

However, from a planning perspective, such methods could exacerbate existing challenges. Current model assumptions about user behaviour, particularly in terms of hourly resolution in both planning and simulation, are unsuitable for effectively capturing individual differences. Should control systems significantly improve by adequately integrating individual behavioural patterns into decision-making processes, this would automatically widen the existing gap between predicted and actual energy consumption. Therefore, improving user behaviour modelling assumptions during the planning and simulation phase is of great importance to accurately estimate the processes of intelligent control systems and the resulting key energy performance indicators of buildings.

Improvements to currently applied methods and models are therefore necessary both for the design and operation of artificial lighting control systems. However, to develop and, more importantly, sufficiently validate current approaches on a generalized level, very large datasets are required, which are, from today's perspective, still far from being available in sufficient quantities. It is important to understand, that this challenge pertains not only to the impact of user behaviour on building performance but also to the understanding of user behaviour itself.

Today, it remains unclear to what extent user behaviour is truly driven by individual factors or whether cultural or organizational influences significantly limit individuality. If the latter is true, it could potentially lead to a substantial reduction in the complexity of user modelling, as only phenotypological considerations would be necessary. However, whether this simplification is feasible, and if so, whether and to what extent existing phenotypes can be transferred across different application areas, has not yet been adequately investigated.

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