Knowledge Discovery Approach to Understand Occupant Experience in Cross-Domain Semantic Digital Twins

Alex Donkers [1], Bauke de Vries [1] and Dujuan Yang [1]

[1] Eindhoven University of Technology, Groene Loper 6, Eindhoven, 5412AZ, The Netherlands

Abstract

Occupant-centric decision-making in buildings requires integrating occupant information with other building information. Semantic web technologies promise to reduce data interoperability issues. However, methods to discover occupants' experiences and integrate those with linked building data are scarce. This paper aims to show how combining knowledge discovery in databases and semantic web technology could lead to an improved understanding of occupants' experiences in buildings. This approach is applied to a case study using the Open Family Home. An occupant collected feedback on various comfort indicators using a smartwatch app. Building information, sensor data, weather data, and occupant information and feedback were integrated into a cross-domain semantic digital twin. A Python script collected all the data from the digital twin and ran a data analysis, after which parameters that affected the occupant's experience were collected. The results were transformed into triples and integrated with the linked building data. This combination of knowledge discovery in databases and semantic web technologies results in enriched digital twins that can be used for occupant-centric decision-making. The approach presented in this study was generalized into a four-step method that can be applied at a variety of use-cases in the architecture, engineering, and construction domain.

Keywords

Linked Data, Semantic Web, Occupant Experience, Semantic Digital Twin, Knowledge Discovery in Databases

1. Introduction

While buildings should be designed to meet the occupants' expectations, research suggests that many buildings fail to satisfy their occupants [18]. Occupant-centric building operations require the understanding of occupants and their relationship with the buildings they use. This relationship is very multidimensional and is influenced by physiological, psychological, and environmental parameters [14]. These parameters are often measured by disparate sources and stored in isolated data silos. Standards to integrate these data and operate buildings are still lacking [18].

Over the last decades, various research initiatives applied semantic web technologies to integrate building information with other (non-building) information. Pauwels et al. [19] and Boje et al. [1] extensively described how semantic web technologies are applied to integrate heterogeneous building information into so-called semantic digital twins. Integrating sensor data with building information enabled researchers to monitor building performance [11,21], reduce energy consumption [13,17], and improve comfort [5,17]. While semantic web technologies to integrate building information and sensors are researched extensively, the integration of occupants is relatively new.

Earlier research initiatives presented methods to measure occupants' feedback [14] and integrate this feedback with linked building data [3]. Other studies used occupant feedback to predict individual occupant preferences [15]. However, an integrated method that combines cross-domain semantic digital twins and knowledge discovery approaches to understand occupant preferences is lacking.

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EMAIL: a.j.a.donkers@tue.nl (A. Donkers); b.d.vries@tue.nl (B. de Vries); d.yang@tue.nl (D. Yang)
ORCID: 0000-0002-8809-3277 (A. Donkers); 0000- 0002-7885-8221 (B. de Vries); 0000-0003-3124-6604 (D. Yang)

Understanding the occupants' behavior and preferences and integrating them with linked building data would support occupant-centric decision-making processes during the operational phase of buildings and improves design feedback.

Therefore, this study presents a method to perform knowledge discovery in cross-domain semantic digital twins. The method was applied in a case study, where heterogeneous data from disparate sources was integrated using semantic web technologies. These data were then used in a knowledge discovery procedure, after which the discovered knowledge was integrated with the linked building data.

Section 2 investigates state-of-the-art research into cross-domain semantic digital twins and knowledge discovery using those digital twins. The research method is based on this review and is described in section 3. Section 4 covers the results of this study, followed by a discussion and conclusion.

2. Knowledge discovery in cross-domain semantic digital twins

2.1. Cross-domain semantic digital twins

The development of semantic web technologies for the AEC industry [19] enabled researchers to expand their digital twins with data from other domains. Boje et al. [1] emphasized the opportunities of cross-domain data integration. Multiple research initiatives integrated sensor data with linked building data to reduce energy consumption [6,13,17], monitor and improve building performance [5,6,21] and optimize comfort levels [3,17]. Integrating system information enables controlling systems based on the data in the digital twin [2,8]. Semantic integration of weather data could lead to enhanced monitoring and control strategies of buildings [5,6,11,13].

The increasing interest in occupant-centric building operations [18] led to the development of semantic web technologies for occupants and their behavior. Nolich et al. [17] semantically represented occupants, including health status and comfort preferences. Li et al. [16] developed an ontology that represents occupant behavior and comfort. Similarly, work by Degha et al. [2] enabled semantic representations of occupants, their states, activities, properties, and preferences. Some recent research initiatives created ontologies to represent occupant feedback [3,12,17,27].

2.2. Knowledge discovery in semantic digital twins

Knowledge discovery in databases (KDD) is defined as "the nontrivial process of identifying valid, novel, potentially useful, and ultimately understandable patterns in data" [9]. KDD processes are applied to derive higher-level knowledge from (raw) data. Fayyad et al. [9] described a five-step model for knowledge discovery, being 1. *Selection*, 2. *Preprocessing*, 3. *Transformation*, 4. *Data mining*, and 5. *Evaluation and interpretation*.

Ristoski and Paulheim [25] and Esnaola-Gonzalez [10] described how semantic web technologies could be applied to enrich multiple steps in the KDD process. First, semantic web technologies could help the *Selection* procedure by integrating data from different data silos. Petrova et al. [21], Esnaola-Gonzalez et al. [6], and Wang et al. [26] applied semantic web technologies to integrate building information with various sensor data streams for this purpose. Semantic web technologies can then be applied in the *Preprocessing* and *Transformation* phases. Examples mentioned in literature [10,25] include methods for outlier detection, handling of missing data, and feature generation and selection. Esnaola-Gonzalez et al. [7] developed the SemOD framework to help data analysts find outliers using SPARQL queries and applied this in cases related to building performance.

According to Ristoski and Paulheim [25], the *Data mining* algorithms themselves hardly incorporate linked data directly. Recent literature presents similar findings and typically performs data mining in a dedicated software layer. Wang et al. [26] applied graph neural networks on semantic digital twins to find room type classifications based on the available information in the graph. Esnaola-Gonzalez et al. [6] used a data mining model to predict indoor temperature to reduce energy consumption by HVAC systems. Petrova et al. [21] applied data mining to find patterns in operational building data.

Esnaola-Gonzalez [10] mentions that the *Interpretation* phase is often carried out by humans interpreting the KDD results based on their domain expertise. However, semantic representations of the results might potentially explain KDD results without human intervention. Both Esnaola-Gonzalez [10] and Petrova et al. [20,21] therefore suggested storing the semantically annotated results of the KDD process in the graph so that the discovered knowledge could be used for design decision support.

3. Method

3.1. Integrating knowledge discovery results with linked building data

Figure 1 presents a stepwise approach to enable the integration of KDD results with linked building data. First, metadata is queried from a graph database (using SPARQL). This data is used to find specific datapoints in other (time-series) databases. Second, a KDD procedure is performed, including the five steps as described in section 2.2. After performing the KDD procedure, the results are translated to RDF triples using the OPO ontology (section 4.3). Finally, the triples can be stored in the graph database using SPARQL INSERT queries, so that the KDD results are integrated with the original linked building data. Depending on the complexity of the use-case, these steps can either be performed separately, or integrated into a single software solution, which would enable online learning. The next subsections describe how this approach is tested in a case study.

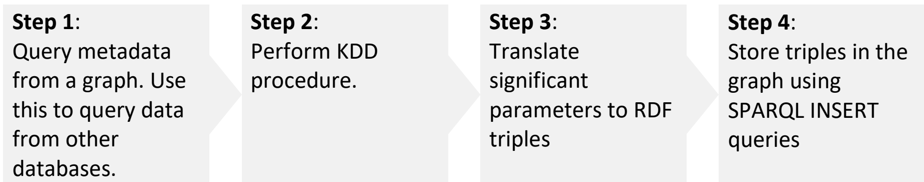

Figure 1: Stepwise approach to integrating knowledge discovery results with linked building data

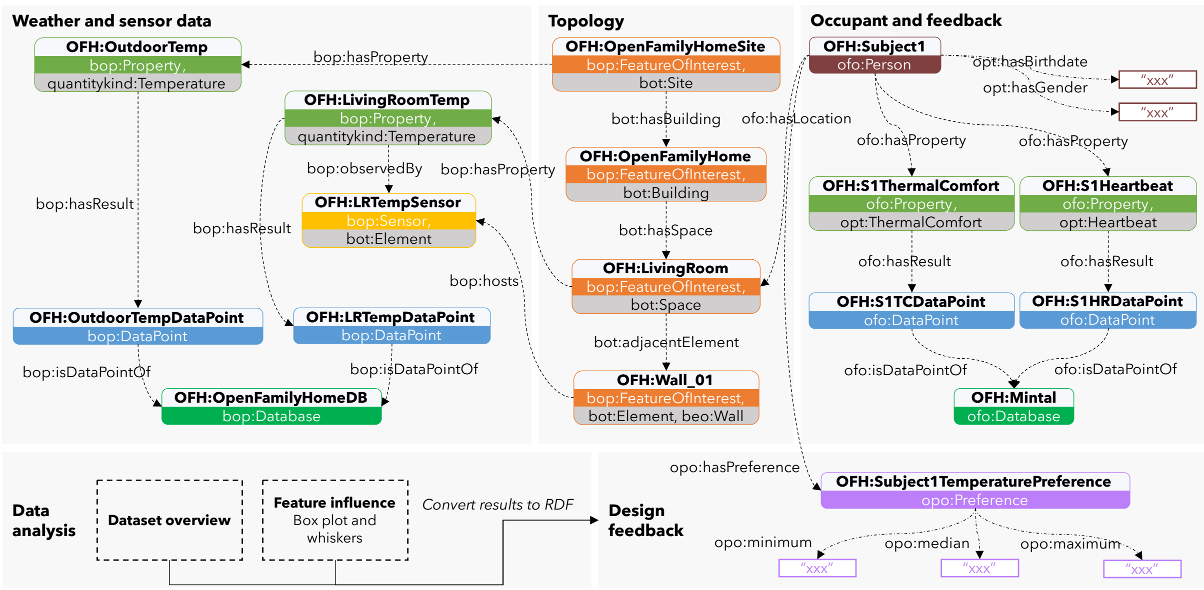

Figure 2: Graphical overview of the research method

3.2. Data collection

A BIM model of a semi-detached house – the Open Family Home – was created using Revit 2020 and converted to RDF Turtle following the BOT [24] and BOP [4] ontologies based on a procedure explained in earlier work [5]. Comfort-related data in the energy performance certificate was manually added to the Turtle file.

Various sensors were installed in the OFH:LivingRoom and OFH:Office to measure illuminance (Eltek LS50), relative humidity and temperature (Eltek RHT10-D), CO_2 (Eltek GD47), and indoor air quality (Eltek GD47AC). A Gen II SRV250 receiver was used to store all sensor data on a local Eltek

Gateway server, after which the data (30.000 measurements per sensor) were written to an InfluxDB cloud database.

A smartwatch app – Mintal [3] – was used to obtain occupant feedback. Two subjects reported 396 feedback responses on air quality, thermal comfort, and visual comfort between January 19 and February 8, 2022. Fitbit's device API provides information related to the user account. While this research does not focus on medical data, the API allows further research into age, metabolic rate, gender, height, weight, and heart rate reports. Meteorological data, including the outdoor temperature, weather type, wind speed and direction, humidity, and air pressure, was acquired via CustomWeather[2].

3.3. Data integration

Based on our findings in section 2.1, semantic web technologies were deployed to integrate all the data. Figure 2 shows a graphical overview of the resulting data structure. The RDF representation of the building's topology forms the core of the linked data. This topology is modeled following the BOT ontology [24] and consists of a bot:Site, a bot:Building, and multiple bot:Storeys and bot:Spaces. The BEO[3] ontology extends bot:Element and was used to model walls, floors slabs, windows, doors, and sensors.

Static properties are directly linked to topological elements using datatype properties, following the level 1 complexity as mentioned in earlier research [5,23]. These static properties include simple geometry, material characteristics, orientation, and identifiers. Dynamic properties include the sensor measurements and weather data. Following suggestions by previous research [8,21], these data were stored in a time-series database (InfluxDB). The graph only contains metadata about those measurements, including the bop:Sensor, bop:Property, bop:DataPoint, and bop:Database.

The occupants and their feedback are described using the OFO ontology [3]. Static properties of an ofo:Person, such as birthdate and gender, are again described using datatype properties. Dynamic properties include sensor data generated by the smartwatch and binary comfort states of the occupant (comfortable/uncomfortable). This research only uses the heart rate sensor and monitors three comfort parameters, namely thermal comfort, visual comfort, and air quality comfort. The data are stored in InfluxDB and the graph contains metadata that helps finding the right data point in the time-series database, similar to the weather and sensor data. All metadata of the occupants and their feedback is automatically generated by the smartwatch app [3].

3.4. Data analysis

A knowledge discovery method by Lee and Ham [15] was applied to determine the influence of individual parameters on various comfort indicators. The method compares the value of a single parameter with a binary feedback state using boxplots. Significance is assumed if the mean value of the parameter during positive feedback lies outside the first quartile and third quartile range of the parameter during negative feedback (and vice-versa). Further elements of reasoning, including a comparison of the central 50%, and the spread and the shift of the boxes, are applied to understand the results [22].

A Python script was developed to query the data from the various databases and perform the data analysis. Static properties were queried directly from GraphDB using SPARQLWrapper[4]. To query the latest state of dynamic properties, we first queried metadata from GraphDB (using SPARQLWrapper) and directly used these results to build Flux queries in InfluxDB (using InfluxDB-Python[5]). Missing sensor readings were replaced by their previous value. After performing the data analysis, significant values are stored as triples using the Occupant Preference Ontology (OPO) and integrated with the original data in GraphDB. This procedure is described in section 4.3.

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[2] https://www.timeanddate.com/weather/
[3] https://pi.pauwel.be/voc/buildingelement
[4] https://pypi.org/project/SPARQLWrapper/
[5] https://github.com/influxdata/influxdb-python

4. Results

Section 4 presents the main results of the case study. The aim of this proof-of-concept study is to test the feasibility of the method introduced in section 3.

4.1. Dataset overview

Figure 3 shows an overview of the collected sensor data during the test period. The sensor data are queried using SPARQL and Flux queries as explained in section 3.4. First, these data could be used to determine a building's performance based on predefined criteria, as shown in earlier work [5]. Secondly, the data helps to understand the occupants' experience of the indoor environment, as shown in the next subsections.

Various conclusions could be drawn based on figure 3. First of all, the OFH:LivingRoom seems to outperform the OFH:Office in both thermal comfort and air quality. The OFH:Office is relatively cold and humid, while also facing higher CO_2 levels and air pollution. This could lead to sick building symptoms. However, the illuminance in the OFH:Office is significantly better than the illuminance in the OFH:LivingRoom. This observation is consistent with the fact that office spaces generally achieve a higher illuminance than living rooms.

Based on those measurements, negative feedback is expected on thermal comfort, visual comfort, and air quality. Since the OFH:Office is likely to produce the most complaints, the remainder of this result section will focus on measurements in the OFH:Office.

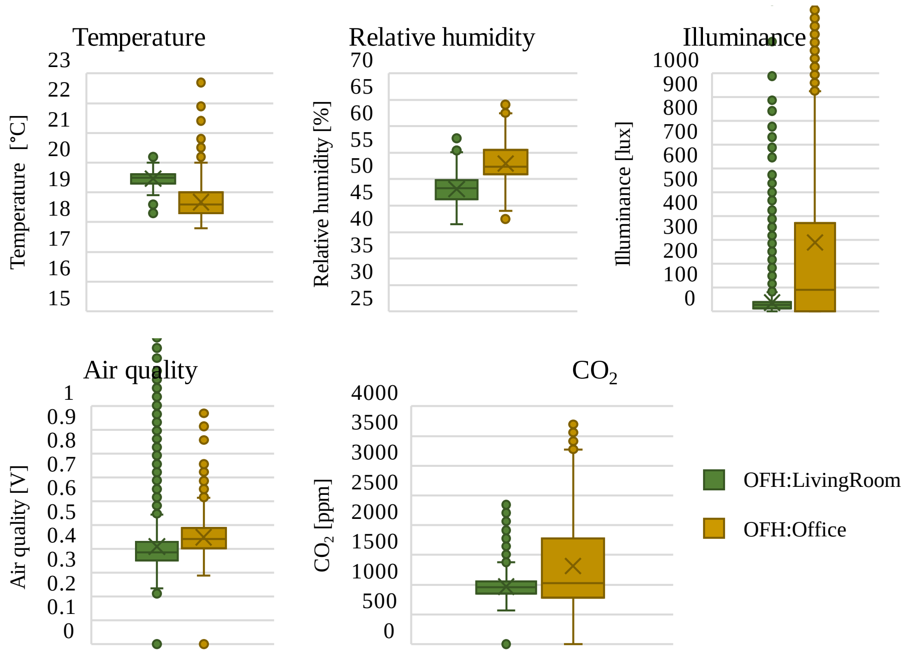

Figure 3: Comparison of IEQ parameters in the living room and the office

4.2. Feature impact

This subsection shows the results of the knowledge discovery method explained in section 3.4. Three analyses were performed to find significant parameters influencing thermal comfort (figure 4), visual comfort (figure 5), and air quality (figure 6), respectively.

Figure 4 shows the parameters that are expected to influence OFH:Subject1's thermal comfort. Remarkably, the data does not show a significant influence of the temperature and relative humidity on the thermal comfort feedback, while standards generally include those parameters in thermal comfort models [15].

The occupant's heart rate, the outdoor temperature, and the time of the day were found to significantly influence the thermal comfort feedback of OFH:Subject1. The low outdoor temperature might cause radiant temperature asymmetry, while higher heart rates often relate to higher metabolic rates (increasing thermal comfort at low temperatures) [15]. Thermal adaptation and outdoor heat gains during the day might cause the correlation between time and comfort feedback.

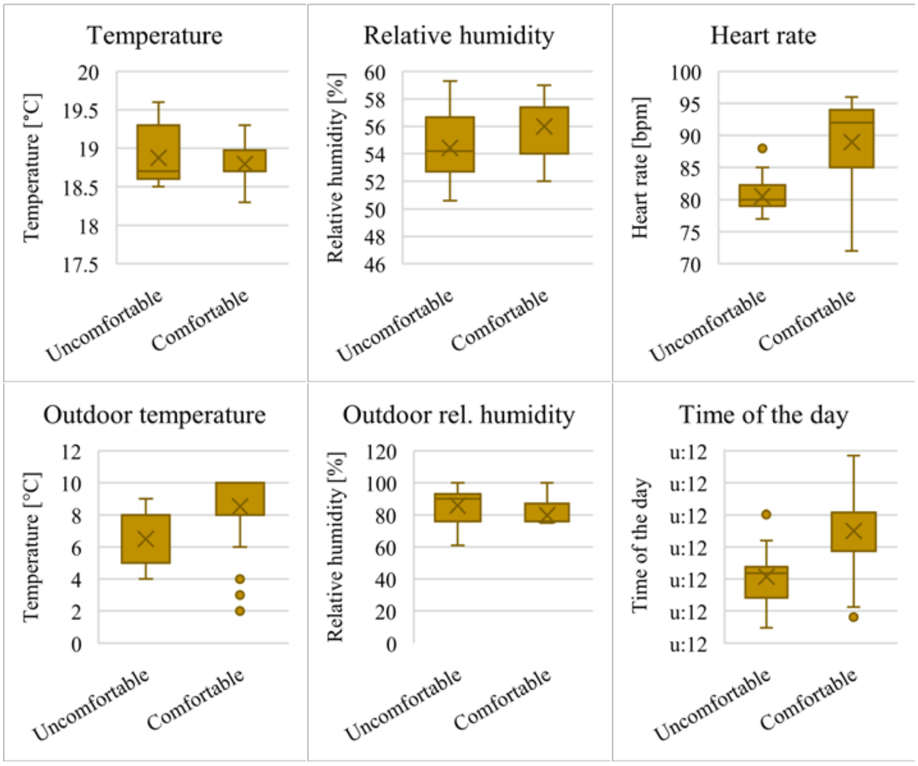

Figure 4: Influence of various parameters on thermal comfort of OFH:Subject1

Figure 5 shows parameters that were expected to influence the visual comfort of OFH:Subject1. Higher illuminance is found to significantly improve the visual comfort. Interestingly, the outdoor visibility (which is lower during foggy weather) strongly influences the visual comfort, as almost all positive feedback was given during non-foggy weather.

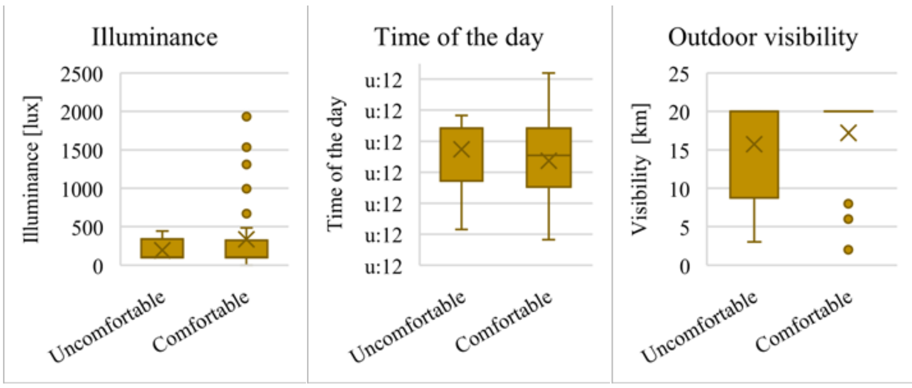

Figure 5: Influence of various parameters on visual comfort of OFH:Subject1

The influence of parameters on OFH:Subject1's feedback on air quality is shown in figure 6. The mean value for uncomfortable indoor air quality lies above the highest observed IAQ value during comfortable feedback, indicating that higher IAQ values (implying higher air pollution) negatively influence OFH:Subject1's feedback on air quality. The CO_2 concentration and relative humidity seem to have no significant influence on the experience of air quality.

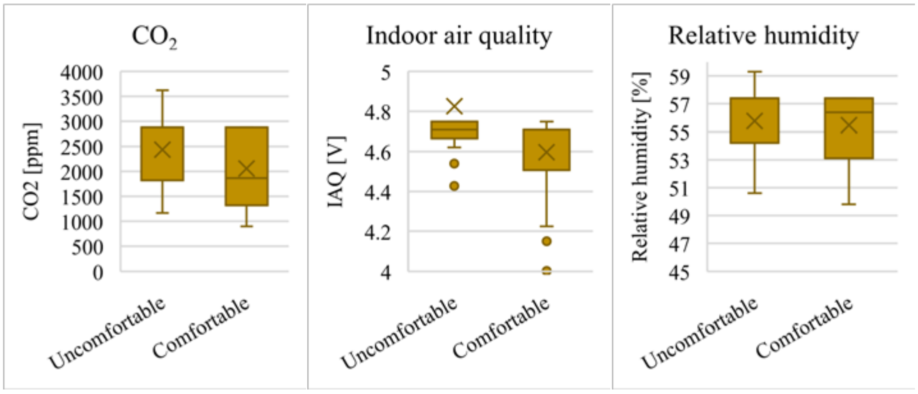

Figure 6: Influence of various parameters on air quality comfort of OFH:Subject1

4.3. Knowledge integration

To be able to use the results of our knowledge discovery method, the Python script that queries all the data and runs the knowledge discovery algorithms ends with translating the significant parameters to RDF triples. A SPARQL INSERT query is used to insert those triples in the GraphDB repository to integrate them with the existing linked building data. The triples are created using string concatenation in Python. This process is automated as it makes use of the metadata that is available in the GraphDB repository. This includes the person, the significant properties, and the comfort property.

The resulting set of triples is shown in figure 7. The purple blocks represent the occupant preferences. Results of the knowledge discovery method are stored as literals and connected to an instance of opo:Preference using datatype properties. The opo:Preference class represents the latest set of preferences on a property. A timestamp is added to the opo:Preference class to enable querying the latest values. The pattern is based on the property state pattern in OPM [23]. The opo:Preference is linked to an ofo:Property using opo:onProperty. It is also linked to an ofo:Person and to the comfort property of this person.

Listing 1 shows how a simple SPARQL query could return the first and third quartile values from the graph in figure 7. The result could be used to assess if the current state of the building fulfills the expectations of the user, and automatically trigger HVAC systems if parameters lie outside the acceptable range.

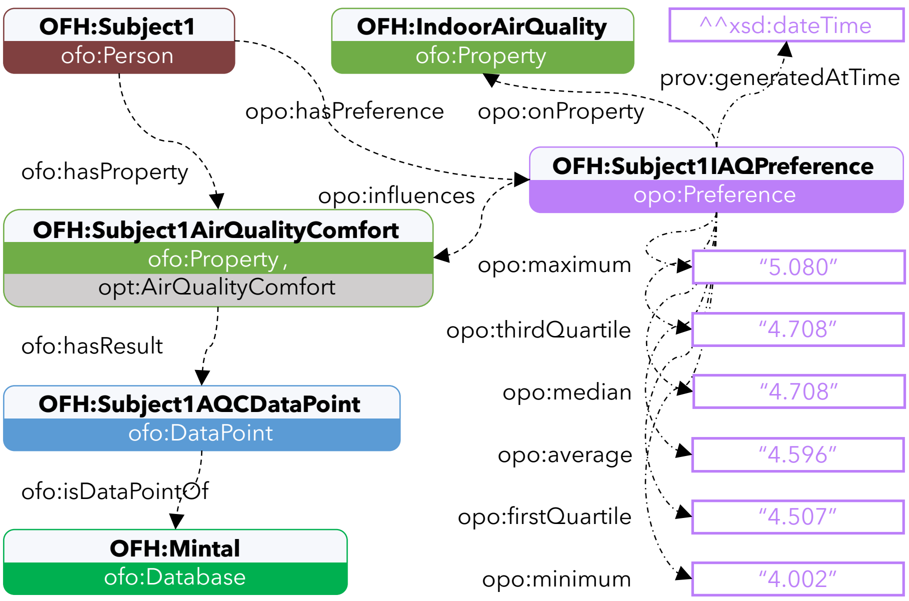

Figure 7: Integrating occupant preferences using linked data

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PREFIX OFH: <https://github.com/AlexDonkers/OpenFamilyHome#>
PREFIX opo: <https://alexdonkers.github.io/opo#>
PREFIX prov: <http://www.w3.org/ns/prov#>
SELECT ?firstQuartile ?thirdQuartile
WHERE { OFH:Subject1 opo:hasPreference ?preference .
?preference opo:onProperty OFH:IndoorAirQuality .
?preference prov:generatedAtTime ?time .
?preference opo:firstQuartile ?firstQuartile .
?preference opo:thirdQuartile ?thirdQuartile . }
ORDER BY DESC(?time) LIMIT 1
```

Listing 1: SPARQL query that finds OFH:Subject1's preferences on OFH:IndoorAirQuality

5. Discussion

This paper aimed to show how combining KDD and semantic web technologies could lead to an improved understanding of occupants' experiences in buildings. The combination of KDD and semantic web technologies enables data scientists to perform cross-domain knowledge discovery procedures that justify the holistic nature of the AEC industry.

The method presented in this paper can be generalized so that it can be used in a wide variety of use-cases. The stepwise approach in figure 1 enables performing KDD on data in semantic digital twins and integrating the results into that digital twin. The approach can be executed using a single script for quick (online) knowledge integration. Step 2 can also consist of a more extensive KDD process. The flexibility of this approach makes it useful for knowledge discovery in relevant research domains, such as energy performance, indoor environmental quality monitoring, and system automation.

The application of KDD in the domain of occupant preferences and behavior is expected to be a recurring process. Not only will occupant preferences and behavior differ per person, but they are also expected to change over time. This includes seasonal changes and aging effects. Building improvements and other building innovations might also influence future occupant preferences. The flexibility of our stepwise approach allows for a quick update of the occupant preference module so that the building could adapt systems based on the latest occupant feedback without significant delays.

This research is a proof-of-concept of the introduced method. To unlock statistically significant results, more data needs to be generated. More in-depth statistical analyses should be used to research the influence of buildings' attributes, environmental parameters, and personal characteristics on occupants' preferences.

6. Conclusion

While buildings can contribute to occupants' wellbeing, there is a lack of knowledge to operate buildings according to occupants' expectations. Integrating heterogeneous data from various sources is necessary to enable occupant-centric decision-making. Semantic web technologies proved to successfully integrate such data into cross-domain semantic digital twins. However, methods to discover deeper insights of occupants' preferences and experiences, and integrate those insights into the graph, are scarce.

Therefore, this paper presents an approach to combine KDD procedures with semantic digital twins. A case study was performed using the Open Family Home. A subject collected feedback on various comfort indicators using the smartwatch app Mintal. Building information, sensor data, weather data, and occupant information and feedback were integrated using semantic web technologies. These data are analyzed using boxplots.

The data analysis presents insights into the influence of individual parameters on the subject's experience of comfort. Significant parameters were translated to RDF Turtle format and stored in the graph. Future work should demonstrate the validity of the KDD results with larger sample sizes of occupants and buildings.

7. Acknowledgements

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8. References

[1] C. Boje, A. Guerriero, S. Kubicki, and Y. Rezgui, Towards a semantic Construction Digital Twin: Directions for future research, Automation in Construction. 114.103179 (2020). doi:10.1016/j.autcon.2020.103179.

[2] H.E. Degha, F.Z. Laallam, and B. Said, Intelligent context-awareness system for energy efficiency in smart building based on ontology, Sustainable Computing: Informatics and Systems. 21 (2019). doi:10.1016/j.suscom.2019.01.013.

[3] A. Donkers, B. De Vries, and D. Yang, Creating Occupant-Centered Digital Twins Using the Occupant Feedback Ontology Implemented in a Smartwatch App, manuscript submitted for publication.

[4] A. Donkers, D. Yang, B. de Vries, and N. Baken, Building Performance Ontology, 2021. URL: https://w3id.org/bop.

[5] A. Donkers, D. Yang, B. De Vries, and N. Baken, Real-Time Building Performance Monitoring using Semantic Digital Twins, in: Proceedings of the 9th Linked Data in Architecture and Construction Workshop, CEUR Workshop Proceedings, Luxembourg, Luxembourg, 2021, pp. 12.

[6] I. Esnaola-Gonzalez, J. Bermúdez, I. Fernandez, and A. Arnaiz, Semantic prediction assistant approach applied to energy efficiency in Tertiary buildings, Semantic Web. 9.6 (2018) 735-762. doi:10.3233/SW-180296.

[7] I. Esnaola-Gonzalez, J. Bermúdez, I. Fernández, S. Fernández, and A. Arnaiz, Towards a semantic outlier detection framework in wireless sensor networks, in: Semantics2017: Proceedings of the 13th International Conference on Semantic Systems, ACM, 2017, pp. 152-159. doi:10.1145/3132218.3132226.

[8] I. Esnaola-Gonzalez, and F. Javier Diez, Integrating building and IoT data in demand response solutions, in: Proceedings of the 7th Linked Data in Architecture and Construction Workshop (LDAC 2019), CEUR Workshop Proceedings, 2019, pp 92-105.

[9] U. Fayyad, G. Piatetsky-Shapiro, and P. Smyth, From data mining to knowledge discovery in databases, AI Magazine. 17.3 (1996): 37. doi:10.1609/aimag.v17i3.1230

[10] I.E. Gonzalez, Semantic Technologies for supporting KDD Processes, Ph.D. thesis, University of the Basque Country UPV/EHU, Leioa, Biscay, Spain, 2019.

[11] S. van Gool, D. Yang, and P. Pauwels, Integrating sensor and building data flows: a case study of the IEQ of an office building in the Netherlands, in: Proceedings of the 13th European Conference on Product and Process Modeling 2020-2021, CRC Press, Moscow, Russia, 2021, pp. 6.

[12] F.M. Gray, H. Dibowski, J. Gall, and S. Braun, Occupant Feedback and Context Awareness: On the Application of Building Information Modeling and Semantic Technologies for Improved Complaint Management in Commercial Buildings, in: IEEE International Conference on Emerging Technologies and Factory Automation, ETFA, 1, 2020, pp. 101-108. doi:10.1109/ETFA46521.2020.9212164.

[13] S. Hu, J. Wang, C. Hoare, Y. Li, P. Pauwels, and J. O’Donnell, Building energy performance assessment using linked data and cross-domain semantic reasoning, Automation in Construction. 124.103580, (2021). doi:10.1016/j.autcon.2021.103580.

[14] P. Jayathissa, M. Quintana, M. Abdelrahman, and C. Miller, Humans-as-a-sensor for buildings—intensive longitudinal indoor comfort models, Buildings. 10 (2020). doi:10.3390/buildings10100174.

[15] J. Lee, and Y. Ham, Physiological sensing-driven personal thermal comfort modelling in consideration of human activity variations, Building Research and Information. 49 (2021). doi:10.1080/09613218.2020.1840328.

[16] Y. Li, R. García-Castro, N. Mihindukulasooriya, J. O'Donnell, and S. Vega-Sánchez, Enhancing energy management at district and building levels via an EM-KPI ontology, Automation in Construction. 99 (2019) 152-167. doi:10.1016/j.autcon.2018.12.010.
[17] M. Nolich, D. Spoladore, S. Carciotti, R. Buqi, and M. Sacco, Cabin as a Home: A Novel Comfort Optimization Framework for IoT Equipped Smart Environments and Applications on Cruise Ships, Sensors. (2019). doi:10.3390/s19051060.
[18] W. O'Brien, A. Wagner, M. Schweiker, A. Mahdavi, J. Day, M.B. Kjærgaard, S. Carlucci, B. Dong, F. Tahmasebi, D. Yan, T. Hong, H.B. Gunay, Z. Nagy, C. Miller, and C. Berger, Introducing IEA EBC annex 79: Key challenges and opportunities in the field of occupant-centric building design and operation, Building and Environment. 178.106738 (2020). doi:10.1016/j.buildenv.2020.106738.
[19] P. Pauwels, S. Zhang, and Y.C. Lee, Semantic web technologies in AEC industry: A literature overview, Automation in Construction. (2017). doi:10.1016/j.autcon.2016.10.003.
[20] E.A. Petrova, AI for Bim-Based Sustainable Building Design: Integrating Knowledge Discovery and Semantic Data Modelling for Evidence-Based Design Decision Support, Ph.D. thesis, Aalborg University, Denmark, 2019.
[21] E. Petrova, P. Pauwels, K. Svidt, and R.L. Jensen, In Search of Sustainable Design Patterns: Combining Data Mining and Semantic Data Modelling on Disparate Building Data, in: Advances in Informatics and Computing in Civil and Construction Engineering, 2019, pp. 19-26. doi:10.1007/978-3-030-00220-6_3.
[22] M. Pfannkuch, Comparing Box Plot Distributions: A Teacher's Reasoning, Statistics Education Research Journal. 5 (2006) 27–45.
[23] M.H. Rasmussen, M. Lefrançois, M. Bonduel, C.A. Hviid, and J. Karlshø, OPM: An ontology for describing properties that evolve over time, in: Proceedings of the 6th Linked Data in Architecture and Construction Workshop, CEUR Workshop Proceedings, 2018, pp.24-33.
[24] M.H. Rasmussen, M. Lefrançois, G.F. Schneider, and P. Pauwels, BOT: The building topology ontology of the W3C linked building data group, Semantic Web, 12.1. (2020) 143-161. doi:10.3233/sw-200385.
[25] P. Ristoski, and H. Paulheim, Semantic Web in data mining and knowledge discovery: A comprehensive survey, Journal of Web Semantics. 36 (2016) 1-22. doi:10.1016/j.websem.2016.01.001.
[26] Z. Wang, T. Yeung, R. Sacks, and Z. Su, Room Type Classification for Semantic Enrichment of Building Information Modeling Using Graph Neural Networks, Proceedings of the Conference CIB W78 2021, 2021, pp. 773–781.
[27] Q. Yang, Y. Zhao, and Q. Yang, Development of an ontology-based semantic building post-occupancy evaluation framework, International Journal of Metrology and Quality Engineering. 12 (2021). doi:10.1051/ijmqe/2021019.