Artificial Intelligence-Based Assistance Systems for Environmental Sustainability in Smart Homes

A Systematic Literature Review on Requirements and Future Directions

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Abstract: Recently, Artificial Intelligence (AI) is becoming more widespread in the context of fostering more sustainable behavior. In particular, in the context of (private) smart homes, such solutions can contribute to more sustainable resource consumption, leveraging the chances of data analysis for ecological sustainability. This systematic literature review investigates potential requirements for data-driven AI applications aimed at enhancing environmental sustainability in smart homes, analyzing 60 selected papers. Key patterns identified include predictive analytics, privacy and security, context-aware features, real-time monitoring, interoperability, strategies for efficiency, personalized user engagement, user interface design, and other behavioral aspects. We highlight advancements in technology that enable more comprehensive applications and identify the need for integrating distinct features to build consumer trust and acceptance. Consequently, we provide a comprehensive overview of current smart home technology and outline future research directions to improve energy efficiency, user comfort, and environmental sustainability.

Keywords: Smart Home, Artificial Intelligence-Based Assistance Systems, Data-Driven Assistance, Environmental Sustainability, Energy Efficiency, Grounded Theory Literature Reviews

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1 Introduction

The rapid advancement of smart home technology starts to transform living environments into intelligent, adaptive, and efficient spaces [CD07]. Using sensors and devices within the Internet of Things (IoT) and advanced data analytics, smart home assistance aims to improve energy efficiency, comfort, and overall household resource management [Gu13]. With these evolving capabilities, there is a growing emphasis on developing data-driven assistance systems that predict, monitor, and respond to users' dynamic needs [Al18], i.e., assistance based on Artificial Intelligence (AI). The integration of predictive analytics and Machine Learning (ML) is a primary driver of these innovations [ZYS16]. These technologies enable smart homes to forecast energy consumption, detect anomalies, and optimize resource allocation, reducing costs and minimizing environmental impact. However, the successful implementation of these technologies requires addressing critical challenges, such as ensuring user privacy and security [CM20], [We10], managing the complexity of context-aware features, and maintaining interoperability and scalability across diverse smart home systems [Pe14]. Furthermore, personalized engagement strategies that cater to individual preferences and behaviors greatly enhance the user experience in smart homes [Ba13]. Effective user interface design, combined with real-time monitoring and feedback mechanisms, can significantly improve user satisfaction and can encourage sustainable energy practices [WH11], [Za24]. Besides, understanding the behavioral and social aspects of user interaction with smart home technologies is also essential for improving user acceptance and facilitating long-term usage [MPA19]. Combining these research strands and foci to enable a comprehensive understanding of relevant patterns for AI-based smart home assistants can ultimately allow leveraging broad consumer acceptance. Therefore we ask:

What are the potential requirements for developing AI-based assistance systems for environmental sustainability in smart homes?

This question guides our investigation into the technological, privacy, and user engagement strategies essential for advancing the acceptance of smart home systems. We opted for a systematic literature review (SLR) to consolidate the current state of research on AI-based assistance systems in this field. By analyzing 60 selected papers, we identify nine key patterns that inform the development of such systems, elaborate on potential use cases for further development, and discuss future research paths. In this way, we contribute to ongoing efforts to enhance energy efficiency, user comfort, and sustainability in smart homes, ultimately paving the way for smarter, more adaptive living environments by leveraging the chances of AI-based systems in this field.

2 Theoretical Background

Smart living refers to the integration of advanced technologies into residential environments to enhance the quality of life, improving efficiency, and leading to higher sustainability [CD07]. It involves creating intelligent, interconnected systems that can automate, monitor, and optimize various household functions, making daily life more convenient, efficient, and environmentally friendly [CD07]. Smart homes, central to smart living, feature interconnected IoT devices that automate and optimize household functions [Gu13]. These devices collect and exchange data, enabling automation and remote control of home functions [Pe14]. Recently, smart living starts to increasingly integrate advanced technologies such as AI and ML into residential environments to enhance quality of life, efficiency, and sustainability [CD07].

The term AI describes technologies aimed at creating systems that perform tasks that often require human intelligence, such as learning, reasoning, and decision-making [HK19]. In smart homes, AI technologies like ML and Deep Learning (DL) are crucial for improving various aspects such as energy efficiency and user comfort [Al18], [ZYS16]. ML involves training algorithms on large datasets to identify patterns and make predictions, while DL uses neural networks to model complex patterns, often requiring large amounts of data [DY14]. Long Short-Term Memory (LSTM) networks, a type of neural networks, are particularly effective for time-series prediction tasks, such as forecasting energy consumption based on historical usage data [HS97]. These AI techniques enable smart homes to analyze sensor data, recognize user behaviors, and make real-time decisions to ultimately enhance energy efficiency and comfort [Ba14]. AI plays a dual role in energy consumption, as it can both reduce and increase usage. On the one hand, AI improves energy efficiency in smart homes through predictive analytics and optimization techniques, forecasting energy usage patterns based on historical data and past user behaviors [Gu19]. For example, ML-based algorithms can predict peak usage times and adjust Heating, Ventilation, and Air Conditioning (HVAC) systems accordingly, reducing unnecessary consumption [Ka20]. AI-based systems can also identify anomalies in energy usage, enabling timely maintenance and preventing wastage [WYA19]. On the other hand, training complex AI models like deep neural networks is energy-intensive, raising concerns about environmental impact [SGM19]. Advancements in efficient algorithms, hardware accelerators, and energy-aware computing are mitigating these concerns, making AI more suitable and sustainable for real-time applications in smart homes [Sc20]. Most existing studies focus on technological advancements or specific applications of AI-based systems for envrionemntal sustainability, such as [Go19] performing an SLR on intelligent user interfaces or [MSA23] focusing on user acceptance and adoption of smart homes. However, a comprehensive review that consolidates those insights lacks. This paper aims to fill this gap by synthesizing current research and identifying key patterns for developing data-driven assistance systems in smart homes employing an SLR-approach.

3 Methods

SLRs aim to provide an overview of a current state of research of a distinct topic [Sn19], particularly enabling conceptualizations in the context of emerging topics [Pa15]. To ensure a well-defined, transparent, and rigorous process, we technically followed the guidelines by Kitchenham [Ki04] and employed a SLR following the proposed steps by Wolfswinkel et al. for grounded theory literature reviews [WFW13]. First, in the define-phase (i.e., specifying key concepts, the context, and inclusion and exclusion criteria [WFW13]), we established the review scope by defining our research question and focus, centered around AI-based smart home assistants for environmental sustainability.

Second, in the search-step, we developed a systematic search strategy to identify relevant literature. This includes selecting appropriate databases, choosing relevant keywords and search terms, and establishing inclusion and exclusion criteria [WFW13]. We used the IEEE Xplore, AISeL, and ACM databases for our search, employing the search term below (* indicates the use of wildcards). Our inclusion criteria ensure peer-reviewed articles available in English. Further criteria provide the focus on smart home applications, particularly related to energy efficiency and sustainability, therefore excluding papers focusing on different fields like Ambient Assisted Living.

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("artificial intelligence" OR "AI" OR "machine learning"
OR "ML") AND (("energy" AND (sav* OR efficien*)) OR
"green" OR "sustainability") AND (app* OR platform* OR
ecosystem* OR "statistics" OR "guideline" OR "framework")
AND ("smart home" OR "smart living" OR "smart building")
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In the third, the select-step, we screened the identified studies to select those that are most relevant to the research question. This involves a two-stage screening process: an initial review of titles and abstracts (i.e., retrieved publications), followed by a full-text review of potentially relevant studies (i.e., retained publications), consistently applying the selection criteria to ensure the reliability of the review process [WFW13]. From AISeL, the search initially yielded 1,393 papers. Filtering by relevance of title and abstract, we retrieved 78 papers and finally retained 17 papers that contained relevant potential requirements. From IEEE Xplore, we initially extracted 640 papers, retrieved 74, and retained 24. From ACM, we initially received 485 papers, retrieved 38, and retained 19. Thus, combined from all sources, we retained 60 relevant papers.

In the fourth phase, the analyze phase, we manually extracted and synthesized data from the selected studies. This step involves coding the data, identifying patterns and themes, and synthesizing the findings [WFW13]. A group of three researchers conducted the coding and evaluated derived results, inductively developing nine reoccurring patterns.

4 Results

The results of this SLR highlight key patterns essential for developing an effective data-driven assistance system in smart homes, i.e., an AI-based assistance fostering environmental sustainability in the smart home context. We identified nine patterns by observing recurring themes in the selected papers, which Table 1 (Appendix) summarizes, providing an overview of the occurrences of these patterns within the papers. The first pattern, “predictive analytics and ML” (P1, #29 papers), underscores the importance of advanced algorithms for optimizing energy consumption and detecting anomalies. The “privacy and security” (P2, #8 papers) pattern emphasizes the need for robust data protection mechanisms to ensure user trust. “Context-aware features” (P3, #18 papers) focus on systems that adapt to user behaviors and environmental changes to improve efficiency and comfort. “Real-time monitoring and analysis” (P4, #31 papers) highlights the significance of continuous data collection and analysis for informed decision-making. The “interoperability and scalability” (P5, #5 papers) pattern stresses the importance of flexible and extensible systems. “Strategies for efficiency” (P6, #43 papers) discusses strategies for improving sustainable energy use and integrating renewable sources. “Personalized user engagement” (P7, #20 papers) explores methods to tailor user experiences and encourage energy-saving behaviors. “User interface and experience” (P8, #14 papers) focuses on creating user-friendly interfaces that facilitate engagement and understanding. Lastly, “other behavioral and social aspects” (P9, #12 papers) examine strategies to influence user behavior and build trust.

Developing data-driven assistance systems enhancing energy efficiency often involves “predictive analytics and ML” (P1), with energy forecasting as a prominent theme. [KKR10], [Re20], and [XW20] highlight the importance of leveraging AI-driven context awareness and IoT data to predict energy consumption, optimize resource allocation, and guide users in energy-saving behaviors. [Ba17] aim at improving efficiency of air conditioning by estimating savings that can be achieved through behavioral energy efficiency initiatives for residential households in a tropical climate. [Bo18] presented a self-learning system, which is capable to inform about negative influences of different HVAC control algorithms. [Ar23] and [Ak24] use LSTM models to forecast energy demand, while [Na21] also forecast supply, considering factors like electricity prices and climatic conditions, showcasing advanced forecasting techniques for both general and cold-climate cities. [Ir23] aggregate the results of multiple ML algorithms using fuzzy operators to provide more reliable forecasts. Another ensemble approach was also used for anomaly detection, where [Ar17] propose an ensemble learning framework for identifying abnormal energy consumption due to equipment malfunctions or human errors, while [Al19] and [Di18] recommend specific ML algorithms and Bayesian Networks for real-time anomaly detection based on occupancy patterns. Another reoccurring theme is behavioral prediction, which is crucial for optimizing energy usage. [FBK12] integrate ML and Semantic Web techniques to predict usage patterns, while [Li15] and [Al16] emphasize activity recognition and personalized recommendations to reduce energy waste. [RMK17] focus on non-intrusive load monitoring to predict user behavior and optimize energy utilization. Finally, thermal comfort prediction ensures occupant comfort while optimizing energy usage. [Ch17] implement classifiers to predict thermal comfort levels. [ZHW19] and [Ak24] further explore DL and LSTM networks for enhancing thermal comfort predictions and energy management.

The “privacy and security” (P2) pattern is crucial for ensuring user trust and safe handling of personal data. [Sa12] introduce the Go Green project, which reduces energy consumption and increases user comfort by modeling user preferences through personas and entities, enhancing privacy by avoiding direct collection of personal data. [GSB22] propose design requirements and principles for privacy-friendly smart energy services, emphasizing user control over data, building trust, adhering to privacy by design, and acting responsibly. Other requirements include reducing data traffic, establishing rigorous access controls, minimizing data collection intervals, and ensuring secure data computation and storage [GSB22]. [MSA23] review factors influencing user acceptance of smart homes, identifying key constructs such as perceived usefulness, ease of use, trust, cost, enjoyment, and perceived privacy and security risks. Addressing these risks through robust measures like encryption and secure data storage can enhance trust and satisfaction, facilitating user adoption. [Me18] focus on IoT security, particularly by identifying compromised IoT devices based on their inherent communication behavior. [Hy19] demonstrate "Sterling", a decentralized data marketplace for secure data sharing and privacy-preserving analytics and ML of individuals' health data. [Ja19] examine the tension between utility and privacy in the context of collecting information on power consumption to increase power efficiency, and [Pa21] address the related tension of privacy and convenience, proposing a model for informed consent and data protection behavior in IoT-enabled smart buildings. Notably, "privacy and security" is one of the least frequently identified patterns, as we found it in only eight of our selected papers. This, together with the insight that perceived privacy is a relevant factor for user acceptance [Ca23], [CM20], [MSA23], indicates that more research might be needed in P2.

"Context-aware features" (P3) enhance smart home functionality by adapting to user behaviors and preferences. [ASM19] and [Ze15] propose adaptive messaging for timely energy-saving advice, while [KKR10] and [SCC21] highlight dynamic control systems that adjust device operations based on real-time data. [WNM13], [Va14], [Li15], and [Fr17] provide personalized advice, integrating user-centered visualization and gamified incentives to induce behavioral change. [Kw14] and [PB17] emphasize user interaction and engagement through eco-feedback and intelligent scheduling. [Al16], [MN19], and [Ca22] address recognizing complex daily activities and situation awareness using advanced analytics and sensor integration. [ACF23] propose a framework for context-aware predictive systems, emphasizing high data quality and strategic sensor selection.

The next pattern, "real-time monitoring and analysis" (P4) facilitates smart home efficiency. For example, [CKP12] and [RMK17] develop systems for detailed energy monitoring and load scheduling, while [KKR10] and [Al16] focus on occupancy and activity recognition. [ZHW19] highlight environmental monitoring for optimal thermal conditions, and [Ar17] and [Di18] focus on anomaly detection for managing energy efficiency. [FBK12], [Va14], [Pa19], and [Ra22] emphasize personalized recommendations based on real-time data analysis, inducing energy-efficient behaviors. [WNM13] and [Fr17] integrate user-centered visualization with context-aware recommendations to engage users and encourage energy-saving practices.

"Interoperability and scalability" (P5) are fundamental for robust smart home systems. [FBK12] and [Fr17] propose open interfaces and APIs for customization and integration, while [SCC21] and [Ak24] emphasize scalable solutions using LSTM networks and cloud frameworks for accurate energy predictions and efficient system performance. As only five papers feature this pattern, we identify a need for future research to focus on this area due to the centrality to address potential lock-in effects for more responsible developments [CH24] and the practical relevance for implementing smart home systems.

The pattern "strategies for efficiency" (P6) focuses on strategies for optimizing energy consumption and integrating renewable energy sources. [KKR10] and [CKP12] present systems for analyzing appliance usage and identifying abnormal patterns, while [RMK17] and [PB17] explore eco-feedback design. [Va14], [ASK16], and [Na21] integrate renewable energy and ML methods to manage energy demand and supply effectively. [Kr19] and [MS23] emphasize behavioral interventions and user engagement to induce energy-efficient behaviors and ensure user acceptance of smart home systems.

"Personalized user engagement" (P7) is crucial for designing engaging smart home systems. [Ch17] propose comfort modeling for optimized HVAC settings, while [Va14], [Li15], and [Ei22] emphasize personalized recommendations. [Fr17] and [Xi21] integrate gamification and incentives to enhance user engagement, while [Da20] and [FYB22] introduce real-time energy recommendations. [WNM13] and [ASM19] highlight the importance of personalized energy visualization and context-aware messaging to prompt energy-saving behaviors. [Kr19] and [BRU22] explore digital nudges and social norms, showing their influence on pro-environmental behavior.

"User interface and experience" (P8) are essential for smart home adoption. [CKP12] and [Ei22] highlight intuitive dashboards for energy consumption insights, while [HBC23] and [MS23] emphasize transparent communication. [FBK12] and [WNM13] focus on multimodal access and personalized energy visualization to drive user engagement. [Ra11] emphasize the ability to use the application anytime and anywhere, adaptability to different sensors, user-friendly interfaces requiring minimal interaction, low cost, and ease of mobility without needing constant internet connectivity. [Fr17] and [PB17] integrate interactive and engaging elements such as gamification and feedback mechanisms to enhance user experience. [Go19] investigated design trends of intelligent user interfaces in the context of contemporary software systems (e.g., based on IoT).

Finally, "other behavioral and social aspects" (P9) are critical for understanding user attitudes towards smart homes. [Kr19] and [BRU22] explore digital nudges and social norms to encourage energy-saving behaviors. [MSA23] identify factors influencing user acceptance, such as perceived usefulness, ease of use, trust, cost, and enjoyment. [HBC23], [Te22], and [Ro13] examine the impact of communication strategies, humor, and various design principles on user trust and engagement. [Za22] aimed at understanding how users envision their desired home assistant and found that they prefer an agent which is highly agreeable, has higher conscientiousness, and emotional stability. [ASM19] and [MS23] highlight the importance of context-aware messaging and real-time feedback for balancing energy efficiency and user comfort. [Sa12] emphasize modeling user preferences and privacy to improve energy efficiency.

5 Potential Use Cases

Building on the patterns discussed in the previous section, we explicitly developed two potential use cases for AI-based assistance systems in smart homes based on the collected information. The proposed assistants address each of the derived key patterns that should ensure high trust and consumer acceptance, therefore being a valuable instrument to foster environmental sustainability in private households by leveraging technological chances. Firstly, consider a family living in a smart home equipped with IoT sensors where an AI-based assistance system can significantly reduce their energy bills (P6). The system predicts household electricity consumption using LSTM models (P1), considering factors like historical usage data, electricity prices, and weather conditions (P3). It then optimizes resource allocation, such as scheduling high-energy-consuming tasks (like running the washing machine or dishwasher) during off-peak hours. The family receives personalized recommendations for saving energy (P7) and can view their real-time data at any time (P4). The family accesses their data via a user-friendly web interface with energy consumption visualizations (P8) and gamification elements for motivating further energy-saving behavior (P9). The system ensures robust performance using open interfaces (P5) and continuing trust by appropriate data privacy measures (P2). By integrating predictive analytics and ML, smart homes can achieve significant energy savings. [Na21] demonstrated the integration of discrete wavelet transformation and LSTM models for managing energy demand and supply, considering factors such as electricity prices and climatic conditions. Similarly, [Ak24] utilized LSTM networks for forecasting energy consumption across various parameters in cold-climate cities, showcasing the effectiveness of advanced ML techniques in optimizing energy usage. These predictive capabilities allow for better planning and efficient use of resources, ultimately reducing costs and environmental impact.

Another potential use case is a resident in a smart home getting a notification by the system (P7) in real-time (P4) due to abnormal energy consumption. Using ML models, the system adapts to the resident's typical behaviors and preferences but detects an anomaly (P1) due to equipment malfunctions or human errors, which the system is able to distinguish (P3). The system acts responsibly and does not collect more data than needed for its tasks (P2) while ensuring reliable performance with potentially changing devices over long periods of time (P5). The processed information is then appropriately visualized (P8) and the system uses digital nudges to induce energy-saving behavior by assessing the potential cause of malfunction (P9). The resident can subsequently react and adapt the devices' settings, leading to more energy efficiency (P6). [Ar17] proposed an ensemble learning framework for reliably identifying abnormal energy consumption cases as described above. [Di18] recommended specific ML algorithms and Bayesian Networks for real-time anomaly detection based on observed behavior. These studies highlight the importance of anomaly detection in achieving optimal energy efficiency, often tailored to individual occupants' preferences and adaptive to changing conditions.

6 Outlook and Implications

This work highlights key patterns relevant for developing data-driven assistance systems for smart homes and, based on the results, potential future research directions: The integration of predictive analytics and ML (P1) offers substantial potential for optimizing energy consumption and improving user comfort. Future research could focus on refining these models to handle diverse conditions, improving forecasting accuracy, and enhancing resource management to achieve cost savings and reduce environmental impact. Integrating these models with renewable energy sources and ensuring they can process data in real-time from numerous sources will be crucial advancements. Ensuring user privacy and security (P2) is critical as smart homes become more data-driven. Future developments could incorporate robust privacy-preserving techniques, giving users control over their data. Educating users about security practices and transparent communication about data usage can support building trust [Ca23]. As only eight of our selected papers focused on privacy and security, we identify the need for further research, given the relevance in the context of advanced digital technologies overall [Ca23], [CH24]. Furthermore, context-aware features (P3) that adapt to users' behaviors and preferences can significantly enhance the smart home experience. The development could prioritize non-intrusive, user-centric approaches for adaptive messaging and dynamic control mechanisms, providing personalized advice based on real-time data to induce energy-efficient behaviors. Future research could focus on enhancements in cross-device coordination and further personalization to improve user engagement and system effectiveness. Real-time monitoring and analysis (P4) are crucial for maintaining smart home efficiency and comfort. Future systems could integrate advanced sensor networks and ML algorithms to provide continuous insights, enabling proactive management and quick anomaly responses. One area requiring further research could be the development of improved data visualization tools and monitoring systems that adapt to changing environments. Developing open interfaces and APIs (P5) is another crucial but underrepresented pattern, needed for creating interoperable and scalable smart home systems. As such frameworks will accommodate increasing data volumes and expand capabilities without compromising performance, whereas only five of our selected papers have focused on this pattern, we see a need for further research. Sustainability and energy efficiency (P6) should remain core objectives. Integrating renewable energy sources and developing sophisticated energy management strategies will reduce reliance on traditional grids and minimize environmental impact. Research could explore innovative algorithms and ML models to optimize energy usage and incorporate sustainable practices. Personalized user engagement (P7) is critical for inducing long-term user commitment to smart homes. Tailoring experiences to individual needs and preferences, along with utilizing gamification and incentives, can significantly enhance user motivation and satisfaction. Future research could employ robust engagement metrics to refine these strategies. Another frequently discussed pattern is user interface design (P8), playing a crucial role in the success of smart home systems. Prioritizing intuitive dashboards, transparent communication, and multimodal access will ensure ease of use and accessibility, empowering users to make informed decisions and adopt energy-saving behaviors. Research could improve user interfaces by focusing more on different communication modalities such as voice and gesture controls. Addressing further behavioral and social aspects (P9) is essential for inducing sustainable energy practices. Strategies such as digital nudges, social norms, and transparent communication can effectively influence user behaviors and enhance smart home technology acceptance. Future studies could continue exploring these dimensions to develop more effective engagement strategies, such as humor or emotional AI. Finally, our results indicate that most publications already cover several key patterns. However, none of them integrates all aspects. Hence, we call for future research assuming a more comprehensive perspective and integrating the set of key patterns to allow for a more nuanced understanding of potential influences on each other.

Our research makes significant theoretical contributions to the fields of smart home technologies, sustainability, and data-driven assistance systems. First, it enhances the comprehensive understanding of patterns supporting the acceptance of AI-based systems in smart homes. By categorizing and contextualizing various, previously isolated patterns, we provide an overview of important features and potential future research paths. Second, our study contributes to leveraging the chances of digital technologies, particularly AI, for fostering more sustainable (user) behavior by supporting their acceptance. We assess energy management as one application scenario of AI-based systems in smart homes, contributing to more awareness development and sustainable use by revealing key patterns for such systems' acceptance. Third, our derived patterns can support the further spread of AI-based assistants in general, seizing the technological chances for consumers. Practically, our findings offer valuable insights for the development of smart home systems that prioritize energy efficiency and engagement. By emphasizing the important patterns, we provide actionable advice for practitioners aiming to design and implement effective smart home systems. Besides, the developed use cases can directly translate to systems in practice. Despite best efforts, this publication is not without limitations. First, this publication intentionally focuses on private (smart) homes. Still, AI-based assistance systems can make a valuable contribution to public smart buildings or smart cities, requiring dedicated future research. Second, we had to focus on several databases for conducting our SLR since searching a discipline exhaustively is beyond the scope of one single publication. We aim to encourage widening our search to further databases. Third, the chosen search procedure requires a fixed keyword set. Therefore, we encourage future research to assess (developing) sets, contributing to the derived knowledge integration, besides particularly focusing on terms such as DL and neural networks, which are commonly used in AI-related titles, to capture a broad set of relevant studies.

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Appendix

Work	Year	P1	P2	P3	P4	P5	P6	P7	P8	P9
		predictive analytics and ML	privacy and security	context-aware features	real-time monitoring and analysis	interoperability and scalability	strategies for efficiency	personalized user engagement	user interface and experience	other behavioral aspects
[KKR10]	2010	x		x	x		x			
[Lu10]	2010	x					x			
[Ra11]	2011						x		x	
[CKP12]	2012				x		x		x	
[FBK12]	2012	x			x	x	x		x	
[OGW12]	2012						x			
[Sa12]	2012		x	x			x			x
[Ro13]	2013									x
[WNM13]	2013				x		x	x	x	
[De14]	2014				x		x			
[Kw14]	2014			x	x		x	x		
[Va14]	2014			x	x		x	x		
[YNF14]	2014						x			x
[Li15]	2015	x		x	x		x	x		
[SR15]	2015	x					x			
[Ze15]	2015	x		x	x		x		x	
[Al16]	2016	x		x	x					
[ASK16]	2016	x					x			
[Ar17]	2017	x			x		x			
[Ba17]	2017	x					x			
[Ch17]	2017	x			x		x	x		
[Fr17]	2017			x	x	x		x	x	
[PB17]	2017			x			x	x	x	x
[RMK17]	2017	x		x	x		x			
[Bo18]	2018	x					x			
[Cr18]	2018						x			
[Di18]	2018	x			x		x			
[Hy18]	2018		x							

[MS18]	2018		x							
[Al19]	2019	x			x		x			
[ASM19]	2019			x	x		x	x		x
[Go19]	2019								x	
[Ja19]	2019		x							
[Kr19]	2019						x	x		x
[MN19]	2019	x		x			x			
[Pa19]	2019				x		x	x	x	
[ZHW19]	2019	x		x	x		x			
[Ac20]	2020		x							
[Da20]	2020						x	x	x	
[Re20]	2020	x			x		x			
[XW20]	2020	x			x		x			
[Na21]	2021	x			x		x			
[Pa21]	2021		x							
[SCC21]	2021	x		x	x	x	x	x		
[Xi21]	2021						x	x		
[BRU22]	2022							x		x
[Ca22]	2022	x		x	x					
[Ei22]	2022	x			x			x	x	
[FYB22]	2022	x		x	x		x	x	x	
[GSB22]	2022		x							
[Ra22]	2022	x		x	x		x	x		
[Te22]	2022							x		x
[Za22]	2022									x
[ACF23]	2023	x		x	x	x				
[Ar23]	2023	x			x		x			
[HBC23]	2023						x	x	x	x
[Ir23]	2023	x			x		x			
[MS23]	2023						x	x	x	x
[MSA23]	2023		x							x
[Ak24]	2024	x			x	x	x			
Overall		29	8	18	31	5	43	20	14	12

Tab. 1: Key patterns: "predictive analytics and ML" (P1), "privacy and security" (P2), "context-aware features" (P3), "real-time monitoring and analysis" (P4), "interoperability and scalability" (P5), "strategies for efficiency" (P6), "personalized user engagement" (P7), "user interface and experience" (P8), and "other behavioral and social aspects" (P9).