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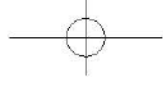


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Aims & Scope

Frontiers in Energy, a peer-reviewed international journal launched in January 2007, presents a unique platform for reporting the most advanced research and strategic thinking on energy technology. In its inaugural year it has published papers by internationally recognized authors in the field of energy development, particularly in China. It aims to promote rapid communication and dialogue among the researchers, scientists, engineers and policy makers working in the areas of energy and power engineering in China and abroad.

The Journal publishes review articles, original research papers and short communications by individual researchers and research groups. The journal is strictly peer-reviewed and accepts only original submissions in English.

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Energy modeling and data structure framework for Sustainable Human-Building Ecosystems (SHBE) — a review

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Abstract This paper contributes an inclusive review of scientific studies in the field of sustainable human building ecosystems (SHBEs). Reducing energy consumption by making buildings more energy efficient has been touted as an easily attainable approach to promoting carbon-neutral energy societies. Yet, despite significant progress in

research and technology development, for new buildings, as energy codes are getting more stringent, more and more technologies, e.g., LED lighting, VRF systems, smart plugs, occupancy-based controls, are used. Nevertheless, the adoption of energy efficient measures in buildings is still limited in the larger context of the developing

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countries and middle income/low-income population. The objective of Sustainable Human Building Ecosystem Research Coordination Network (SHBE-RCN) is to expand synergistic investigative podium in order to subdue barriers in engineering, architectural design, social and economic perspectives that hinder wider application, adoption and subsequent performance of sustainable building solutions by recognizing the essential role of human behaviors within building-scale ecosystems. Expected long-term outcomes of SHBE-RCN are collaborative ideas for transformative technologies, designs and methods of adoption for future design, construction and operation of sustainable buildings.

Keywords sustainability, building energy modeling (BEM), occupant behaviors (OB), sustainable ecosystems, System for the Observation of Populous Heterogeneous Information (SOPHI)

1 Basic overview

1.1 Sustainable human building ecosystem (SHBE) and its constituent elements

The Paris Climate Accord signed by 197 parties of the convention and ratified by 160 members out of 197 in December 2015 [1], is indeed a positive step toward low carbon development. To achieve low carbon development, it is of paramount importance to understand the development of human-building ecosystems, the policy framework that influence such ecosystems and ultimately the consumer behavior on which the development is dependent upon. Here, we propose an innovative and exhaustive Data Structure framework for SHBE. Currently, among scientific community and industry, there exists ambiguity about how to understand occupant behavior (OB) (energy related OB/thermos-physical behavior related to thermal comfort (diet, clothing, movement)/ energy usage patterns) and also contextual factors which directly or indirectly influence all such behaviors. Which data should be collected? Moreover, what is the impact of policies collectively and individually? How to identify metrics and indicators of contribution of OB on SHBEs? How to identify social and policy factors that drive changes on OB? How to evaluate impacts of different policy initiatives/ incentives on OB? This data structure will provide the necessary framework to categorize and identify which data and metrics need to be collected and studied further. The framework also intends to study interaction between final reduction goals of policies and the impact of individual policies on SHBEs.

The goals of this paper are: ① to expand the interpretation of mosaic relationships and intercommunication between mainstay factors of human-building ecosystems; and, ② to promote efforts to develop new

theories and methods for the integration of predictive models that will enable the generation, exploration and validation of new hypotheses that explain and/or promote more sustainable building ecosystems. These goals are the foundation of Sustainable Human Building Ecosystem Research Coordination Network (SHBE-RCN), supported by US National Science Foundation [2]. The SHBE-RCN encompasses interdisciplinary researchers from the US and other parts of the world who are working on common themes—five in total as outlined below—in pursuit of these goals. The SHBE collaborators are sharing and participating in research to define a new and innovative interdisciplinary field called as SHBE that blends OB and social sciences with monetary sciences to the study of design, engineering and meteorology of buildings for proving the evidence of building energy consumption and occupant comfort. The participatory approach and systemized podium to assimilate data will seriously lower the ambiguity affiliated with prognosis of individual acclimation with energy-efficient and sustainable building designs.

It also targets core concern such as “what are the advantages of green construction expenditure to individuals at personal, business, community of government planning level”? The actions of SHBE-RCN consist of ① the collective development of unanimous system for enabling a virtual grid of knowledge based research podium permitting to share connectivity mechanisms from distinct setups of building environment aspects, ② creation of a structured system for recruiting new researchers to the SHBE association, ③ determination of emerging investigation directives for demanding SHBE subareas, ④ evaluation of the successes of the SHBE association, ⑤ development of innovative SHBE curricula to build the academic foundation among graduate students from diverse backgrounds for future research in SHBEs.

The SHBE network focuses on five theoretical themes of fundamentals that comprise of all the elements of SHBE as illustrated in Fig. 1 and yet are interrelated: Theme I—Building Environment Modeling and Physical Systems; Theme II—Modeling Energy Related OB; Theme III—Modeling Impact of Social/Policy Issues; Theme IV—Modeling Dynamic Life Cycle Assessment (LCA) and Business Ecosystem; Theme V—Model Assimilation and Confirmation.

These themes are designed to develop collaborative research podium focused on curbing points of congestion in engineering, software and social/economic sciences that hinder to adoptability of sustainable building practices in our society. This multipronged approach emphasizes the interdisciplinary model for interaction and integration. The focus of theme I activities is to interface with other themes in order to facilitate collaboration on the best methodology for interoperability among the sustainable building processes. The interface process includes the better quantification of human behavior which are outputs of theme II and supply of energy consumption data which serve as input

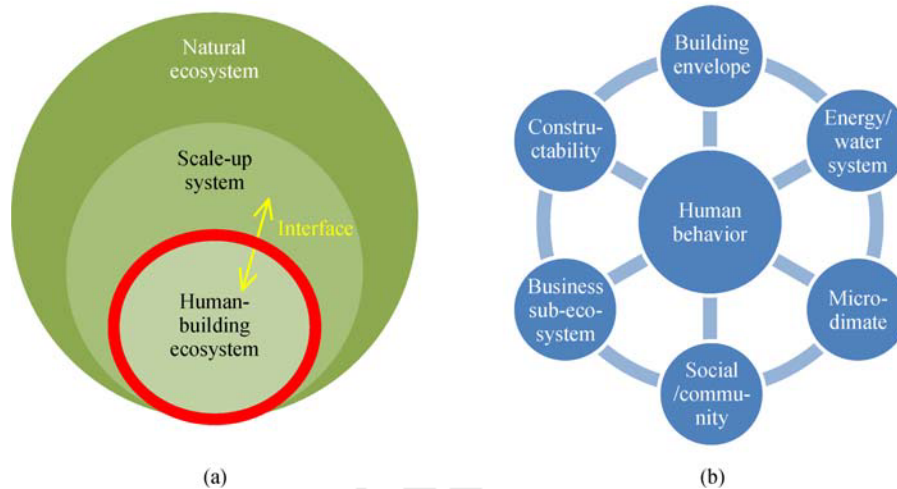


Fig. 1 (a) Correlation between natural ecosystem and its components with interface acting as intermixing between habitat and ecosystem; (b) SHBE conception and its sub elements

for theme III and all these components are required as inputs for interfacing with theme V. The interface elements for theme II correlates human behavior model outputs to theme I, III and V and inputs from all other themes. Theme III focuses on diffusion of technology and diffusion of ecosystem concept to policymaking process and its impact on human building ecosystem. Theme III will provide output for theme II and IV while use inputs from Theme I. Theme IV focuses on LCA by understanding ramification of assimilating OB factors at building or community scale while modeling human-building ecosystems. Theme IV will require inputs from I and II and provide inputs to theme III and V. Theme V ultimately assimilates all interface elements from all other themes and will contribute in developing a standardized data structure which will support new modeling methodology to enable effective integration of interdisciplinary data models and validation of model predictability.

1.2 Motivation

By fostering more SHBEs, dependence on nonrenewable energy sources can be significantly reduced, and the absolute amount of carbon emissions can be decreased. These two achievements are important in order to provide a desirable living environment for future generations of people. By pursuing a better understanding of SHBEs and their implementation in the society, the SHBE-RCN will help to bridge the learning gap between present society and an envisioned future.

1.3 Hypothesis/research question

The SHBE-RCN proposed that integrating energy related OB with the actual performance of physical systems in buildings could lead to serious reduction in the ambiguity

in forecasting models for energy efficiency in SHBEs. In addition, integrating building OB and social and policy factors with building technology and design using a multidisciplinary approach provides important insights to stakeholders.

1.4 Research focus/ objectives

This investigation structure has twofold focus: ① improving knowledge about effective modeling and simulation – and the reliability of associated understandings and predictions – of building energy consumption throughout the design process, and ② understanding the approaches and impacts of integrating learning sources from multiple disciplines to promote cyber-enabled learning of data-driven sustainable building design.

The primary target of SHBE-RCN is to expand coalition based investigation podium designed to overcome barriers in engineering, architectural design and societal/monetary sciences that hinder the broader utilization, adoption and subsequent performance of sustainable building solutions. Expected outcomes of SHBE-RCN include: ① systematic approaches; ② scalable methods for data collection, sharing and analysis; ③ quantification of user behavior on energy usage, perception and adaptation; ④ identification of essential factors and system components.

2 State of the art of the SHBE

In the following, relevant research associated with each theme of the SHBE-RCN is explored. What will be evident from the presentation is the insular nature of relevant nature. The presentation will highlight and motivate the need for integrative research to fill gaps in understanding related to the design, engineering, construction and

operation of sustainable building-scale ecosystems. Characteristic of the required research is the integration of human psychology, communal values and monetary values in conjunction with the study of designs of buildings and engineering and metrology for confirmation of building energy consumption and thermal comfort.

2.1 Theme I—building environment modeling and physical systems

Current research related to building physical system and environment modeling is varied. Most research occurs at one of three levels: materials, building operations, and design optimizations. What is characteristic of these levels is their engineering orientation connected to physical system and environmental modeling. Three representative examples of such are highlighted in the following.

Building materials research and design as connected to energy consumption and OB have long been a focus of sustainability research. For example, Batista et al. [3] synthesized conjointly performing characterization of thermochromic VO₂ thin films when they grew on float glass coated with SiO₂. Thermochromism is the property by which certain material changes its color based on a change in the temperature of the surface. At lower temperatures, vanadium behaves like a semiconductor and blocks infrared transmission in order to reduce energy consumption from windows. At high temperatures, vanadium behaves like a conductor and provides high reflectivity to the glass. Batista et al. achieved deposition of VO₂ on the glass by reactive DC and pulsed-DC magnetron sputtering. The semiconductor-metal transition temperature of 68°C for window application is too high, so Batista et al. developed an approach to bring this temperature down to atmospheric temperature. Batista et al. conclude that W doping with VO₂ coating gives optimum performance for energy efficient window application.

Relevant research in building energy simulation is beginning to integrate (Object-Oriented) Building Information Modeling (BIM) and Object-Oriented Physical Modeling [4]. For example, a BESTEST Case 600 building with a single thermal zone was simulated with Object-Oriented Physical Modeling by creating the BIM2BEM framework [5,6]. The BIM2BEM framework was tested by making the Revit2Modelica prototype. Here, BIM incorporates solar and infrared absorptivity along with frame-ratio of glazing systems, which are made available by Modelica building library developed by LBNL. The Revit2Modelica prototype tests and validates interoperability of BIM and Building Energy Modeling (BEM) and automates thermal simulation.

We contend that sustainable building design, by definition, should be an interdisciplinary activity. Relevant research is moving in this direction as illustrated by this third example. An Architectural Multi-Objective Optimi-

zation (ArchMOO) framework has been proposed in order to incorporate non-quantifiable objectives into Multiple-Objective Genetic Algorithm (MOGA) for sustainable building design [7]. Frameworks like ArchMOO will help architects to participate in the optimization process more cohesively and make decisions on sustainable design by incorporating non-quantifiable objectives like aesthetics and self-expression of design. Such frameworks can incorporate comparative algorithms, like shape comparison algorithms in MOGA incorporated into ArchMOO, for diversifying objectives in Pareto Optimal solutions. This can be achieved by utilizing the Non dominated Sorting Genetic Algorithm-II (NSGA-II) method for reducing optimization time and using Interactive Design Maps for visualizing high dimensional Pareto Optimality. A visual programming based platform, "Optimo," which is a Multiple Objective Optimization (MOO) tool, has been developed [8]. This tool was developed to primarily interact with major BIM authoring tool Autodesk Revit. Optimo uses NSGA-II. Using Optimo, it was found that the performance of NSGA-II for optimizing multiple objectives with respect to multiple parameters is acceptable and presents valuable results.

Parametric studies are essential for design optimization. A case study in Al-Bahr Towers in Abu Dhabi with complex kinetic facades has been performed [9]. The effect of opening ratios of the complex kinetic facades and the solar heat gain of a partial Al-Bahr Towers sample model was investigated. For the solar study, a visual programming tool—Dynamo for Revit was utilized with Rhino/Grasshopper and DIVA for parametric geometry modeling. The study concluded that complex kinetic facades consume 4% less energy than the fixed facades.

2.2 Theme II—modeling energy related OB

Interdisciplinary social science research will not only stipulate serious factual knowledge but also assist in strategy evolution [10,11]. Blending insights and methodologies across disciplines will help provide a more holistic understanding of occupant decision making, behavior, and energy consumption. A social-psychological perspective will account for, for example, how thermal comfort, attitudes, social norms, and other factors contribute to energy behaviors, and can therefore fill in the gaps between simulated models and actual building energy consumption. Three serious limitations have been identified in existing energy research [10]: an over-emphasis on technological as opposed to social factors that predict energy use; disciplinary chauvinism that prefers physical sciences and engineering over social sciences; and a homogenous perspective that stems from most published work originating from mostly male researchers examining problems in affluent, Western, industrialized areas. Indeed, the effect of the human dimension on residential energy consumption, including

the effects of risk perceptions, energy attitudes, altruism, and social norms still requires more investigation [12]. Greater consideration of problems of energy poverty and unequal access to energy services in poorer countries is necessary [13]. A severe knowledge gap exists in addressing the problem of potential technological advances and customer adoption of those critical technologies [12,14]. For example, a more comprehensive analysis of social-psychological and economics factors on OB in both commercial and residents buildings requires more attention from researchers [15,16]. The SHBE-RCN has increased focus on patterns pertaining to human behavior in an attempt to address these limitations in the existing body of knowledge. Better understanding of the dynamics of energy problems from a social-psychological perspective can help guide energy modeling and building design and encourage low-energy operation in buildings.

The potential “rebound effect” and principal-agent problem (where building occupants have little control over energy usage) can be better resolved by social sciences rather than by technical sciences [10,17]. Current decisiveness and choice, acceptance and implementation of modern techniques are dependent on uniform and non-expert judgements/assumptions of energy researchers about human behaviors [18]. Initiatives for energy efficiency use “interventions” for affecting customer behaviors to achieve energy savings, but generally, such interventions are investigated without analyzing fundamental behavioral elements regarding energy consumption. The common discrepancy between attitudes and actions need to be considered and systematically investigated for each, specific energy-related behavior [19,20]. A powerful assessment scheme needs to be developed to capture fundamental human behavior traits related to energy consumption. Antecedent interventions when combined with consequence interventions produce maximum results. Classification of target actions and groups has greatest energy-saving caliber. Focus should shift from micro-level MOA-model (Motivational factors, abilities and opportunities) to macro-level TEDIC factors (technological developments, economic growth, demographic factors, institutional factors and cultural developments). Multi-disciplinary research efforts including environmental scientists and social scientists with focus on macro-level factors is needed, as these factors form real groundwork and technological equipment. Assessment of interventions’ impact should be analyzed and reported based on changes in fundamental factors of behaviors and changes in energy-associated actions. It is very important to report specific behaviors, which are targeted using clearly defined interventions. Large sample sizes should be assessed in order to produce statistically significant data and interventions should be monitored for significant amount of time. Ample statistical data should be reported which is required to calculate the effectiveness of interventions in order to do meta-analyses of those results [21,22]. A DNAS frame-

work has been proposed which considers Drivers, Needs, Actions and Systems of Occupant using obXML schema. The aim of this framework is to provide a common ground for all stakeholders in the green building paradigm to share information and incorporate OB into energy modeling effectively and accurately [23].

Based on the recent publications, it can be said with confidence that research related to the modeling of heating, ventilation, and air-conditioning systems (HVAC) is fairly mature and varied, as different methods have been explored to model HVAC performance/behavior. Most reviewed articles preferred commercial or office buildings for the focus of OB studies [24,25]. Office studies involved: lighting studies [24]; Agent-Based Modeling (ABM) [25]; Data mining [26–29]; and, OB studies focusing various areas [30–32]. Residential studies involved: machine learning [33,34]; OB [35–37]; and, occupant systems [38,39]. The industry and academia need to collaborate more in terms of utilizing the joint capabilities in building simulation. The simulation techniques used in industry does lack deeper statistical and building performance simulation which are performed in academia i.e. the performance gap analysis performed by industry lacks advanced techniques [40,41]. High performance office buildings in the US, EU, and China pacific regions were analyzed based on impact of the climate, building size, efficient technologies, OB, and operation and maintenance. No particular factor was identified as the one affecting performance while all factors have a combined effect on the performance mismatch, e.g., OB and operation and maintenance of the buildings can have a significant impact on building energy consumption [42]. Occupants can lead up to 2.5 times more energy consumption and increased CO₂ levels indoors. Occupants should be encouraged to open windows in morning and evening for thermal comfort; operate blinds for daylight usage; use energy efficient appliances. The window-to-wall ratio should be more than 70% and thermal mass should be exposed to window above the working plane [43]. A building design intended toward low initial cost is the worst in terms of energy consumption and thermal comfort while exhibiting higher operating costs while the building design with high initial costs can accommodate more energy conservative measures and thermal comfort issues leading to lower operating costs and environmentally sustainable [44]. The overtime occupancy schedules model is proposed and tested by hybrid calibration method for integration with energy modeling software. The overtime schedules can satisfactorily predict overtime occupancy [45]. To connect human and behavioral properties, Kingma and van Marken Lichtenbelt [46] studied metabolic rates of females and thermophysical analysis of female thermal comfort. The authors contend that current thermal comfort models, gender discrimination, and the actual metabolic rates of females should be considered in order to adjust the thermal comfort models.

The authors propose a novel model which incorporates actual metabolic rates which predict thermal comfort for them fairly accurately. To achieve thermal comfort the thermal balance should fall into thermoneutral zone. The authors found that the thermal range of 23.2°C to 26.1°C when the mean skin temperatures lie between 32.4°C $\leq T_s \leq$ 33.6°C. Indirect passive human behavior has been studied and integrated into energy modeling. Plugwise wireless smart meters were used for collecting energy data while Fitbit Flex pedometer with Bluetooth. These techniques were implemented to identify OB in terms of occupied/unoccupied and active computer use/idle work situations. C4.5 algorithm performs well for predicting OB. After implementing observed occupancy group schedules with identified patterns on US Department of Energy (DOE) medium size office buildings with 17 different climate zones, it was found that 8.39% increase in heating energy, 2.80% decrease in cooling energy and 4.07% decrease in fan energy for all climate zone [47]. The authors present here four levels of occupant related parameters and the models used to predict behaviors based on those parameters. Cumulative distribution functions (CDFs) were used for occupancy state of space while inverse function method (IFM) was used for predicting the number of occupants in the space. Markov chains were implemented to identify the location of occupants in a space. A software architecture has been developed and is dynamically linked to energy modeling software by using Dynamic Link Library (DLL) function. The proposed architecture would be used for co-simulation with different energy modeling software while implementing wide variety of OB [48]. Eighteen student dormitories at Virginia Tech University were studied and interventions were designed to change OB in terms of water consumption in dormitories. Statistical testing was done by Repeated Measures Analysis of Variance (RMAV) model and Honestly Significant Difference (HSD) pairwise comparison test for comparison between study group and control group. The combination feedback of gallons and associated estimated embodied energy had a significant impact on reducing water consumption usage among residents rather than during feedback of only gallons [49].

An OB framework based on contextual factors has been proposed and the authors believe that instead of considering occupants as unreasonable beings, their behavior should be considered as the one, which is adaptive.

Occupants always try to adapt to the surroundings by changing their behavior and this adaptive changes are based on contextual factors [50]. The existence of inter-building effect; peer network effect and network synergy effect was examined and found effective in energy saving potential by hanging behaviors of people [51]. In a recent study [52], found that contextual factors (group norms and organizational support) interacted with energy saving attitudes and influenced employees' willingness to save energy, especially their willingness to communicate with coworkers about saving energy. Three-parameter Weibull distribution model was used to study Chinese residential behavioral pattern in terms of AC usage. Environmental triggers like indoor temperature and event triggers like opening/closing doors have an impact on AC usage while some random triggers also have influence but can be ignored. The model accurately predicted usage patterns [53]. Data mining techniques were applied to analyze the OB related to thermostat settings and heating set points setting of 62 unit residential building in Revere, Massachusetts, USA. Clustering approach and decision trees were used to achieve this goal. Space heating usage did not show any specific change during 24 h use cycle, and during weekdays, the usage was mostly stable. The heating system cycled a lot during its operation on weekdays and run time of one cycle was found to be very short. That led to the inefficient operation of heating systems in this building. Data mining techniques were found to be an effective measure to predict and analyze OB for the heating season [54].

The biggest effort of the SHBE-RCN is to provide an idea about which kind of data to collect and specific aim of Theme II is to identify which exact OB affect energy consumption or which factors trigger OB, which eventually transform into direct action (energy consumption). Below Table 1 refers to contextual factors affecting OB for particular operation (opening/closing window and energy consumption). Table 2 compiles the factors, which contribute to adaptive behaviors of occupants inside the built environment. Table 3 describes the driving factors, which cause actual OB. Though more such driving factors related to each individual occupant, behaviors need to be identified and their effects should be examined individually or in combination. The OB in itself needs to be identified and studied as an effect of driving factors and contextual factors.

Table 1 Contextual factors affecting OB

	Energy consumption
Indoor air temperature [26,35,53]	Window opening/blinds [26,35,39,44]
Outdoor air temperature [26,35]	Thermal comfort [26,35,46]
Arrival time in office and morning (hour of the day) [26,35,53]	Window blinds [39]
Presence of occupants [26,35]	Occupancy [43–45,48]
Leaving time from office and evening (hour of the day) [26,35,53]	Lighting [39,44]
	Office appliances [47]

Table 2 Factors affecting adaptive behaviors

Factors for adaptive behaviors	
Shared vs. open plan offices [50]	Venetian blades vs roller blades [50]
Number of occupants in space [50]	Ease of using controls [39,50]
Visual comfort [50]	Acoustics [50]
Social constraints [50]	View to outdoors [50]
Availability of energy feedback systems [31,33,37,49,50]	Interior design (presence and location of furniture) [50]
Availability of manually operated systems [50]	

Table 3 Driving factors

Drivers for OB	
Outdoor climate [36,43,42]	Indoor air humidity [36]
Dwelling type [36,53,54,49]	Dwelling age [36]
Dwelling size [36,43]	Room type [36]
House insulation [36]	Type of heating/cooling system [36,42,43,54]
Type of temperature control [36,54]	Type of heating fuel [36]
Occupant age [36]	Occupant gender [36]
Occupant culture/race [36]	Occupant education level [36]

2.3 Theme III—Modelling impact of social/policy issues

This theme addresses four interrelated questions: ① what are the relevant policies, practices and social psychological and economics factors for influencing the energy efficiency and sustainability of human-building ecosystems? ② what factors explain the emergence, adoptions and successful implementation of these actions by governments, organizations, and social groups? ③ how do these actions support (or impede) energy efficiency and sustainability of human-building ecosystems? and ④ what are their impacts on buildings, technology, and behavior across individual, organizational, and city scales?

The modeling work includes analysis of cumulative achievements of the neighborhood that leads to the establishment of inception and propagation of relevant behaviors within the building ecosystem and analysis of inherent activity such as comprehending future ramifications of new technologies. Research also addresses the determinants of the performance of policies aimed at adoption and integration of new technologies, pro-environmental behavior and greater efficiency of SHBE. The employed methodology includes mathematical modeling, econometric analyses and field experiments with data from actual users.

Theme III focuses on understanding the diffusion of the SHBE concept and technologies within social and political systems [55]. The adoption and diffusion of innovative technologies that involve multiple actors (i.e. households, firms, governments, non-profit organizations, and the media) operating at multiple scales. Stochastic network analysis provides tools to model this complexity. The links among actors in these networks can be modeled as spatial

or relational. The synergy between an individual and its habitat is a specific aspect affecting policy action and individual behavior. Theme III connects theories of social, technological and public policy diffusion with real world outputs and outcomes to understand how actors interact with each other across the spatial scale to shape human-building ecosystems. Through behavioral experiments and econometric analysis of community level adoption of green building and energy conservation policies and practices new insights are gained that can enhance the capacity to initiate innovation aid in repairing modeling process of advanced techniques for decreasing uncertainty and boost results.

The environment in which the behavior occurs as well as the objective functions shapes human behavior. Individuals, non-profits, firms, and governments make decisions based on a designed set of options and incentive structures. The options that are made available to individuals are typically constrained by barriers of information, cost, and motivation. Policy, collaboration, and other tools can be used to overcome barriers and restructure incentives for particular behavior between and within all of these entities. These can be viewed as a set of institutions that constrain human behavior or provide additional options that are more effective. Institutional variation exists across local government, cultural context, and policy arena. Examination must occur over many dimensions so that synthesis of these impacts can be drawn and brought together. Dissemination or ratification of sustainable building practices can be seen as societal change. The advancement of such a societal change depends of social acceptance, federal policies like EPA-Energy Star Program, non-profit organizational initiatives (USGBC), news coverage and

local governmental programs (e.g. Green Sense Program-Support for home modifications). Bureaucrats often depend on homebuilders' judgement of success of programs to encourage energy efficiency. Human interaction with environment obviously affects their social functions in general but it affects human behavior in particular. A slight change in environment leads to change in function succeeded by social change. There are some predictable effects of new technology, but some effects are unpredictable. These unpredictable effects may be valuable, or they may have detrimental ramifications, which can reduce efficiency of new technology. Social pilot studies can produce data, which could be helpful for cost-benefit analysis of each initiative. This will lead us to revise the layout and architecture of new technology for increasing performance.

Governmental actors are primary agents for enacting policies to promote SHBE, but they are not the only agents for promoting innovation. The rapid adoption and diffusion of city-level energy and sustainability programs in the absence of strong state or federal incentives, has been a puzzle because programs like green building initiatives contradict the expectations of collective action theory's prediction that local governments will free ride on the efforts of others [56]; even though collaboration across sectors and across scale may be necessary for successful programs. Cities overcome collective action problems because sustainability programs produce local, community-specific and household specific benefits, such as the reduction of energy costs, and healthier, livable communities [57].

Although the US DOE increasingly relies on local governments for execution of energy protocols, local governments have struggled to carry out one of the key goals of these programs in a timely manner [58,59]. Capacity to implement policies varies widely among governments. The lack of technical, fiscal and administrative capacity often impedes both policy adoption and program implementation [60,61]. Urban planners face delivery dilemma in contemporary metropolitan areas. Rich and more ethnologically compatible communities in the USA usually adopt sustainable building practices. Political closeness, climate advocacy and expansion interests significantly help spreading sustainability projects routinely [62–64]. This research found that prosperity and schooling affect policy dispersal, but they do not ordinarily elucidate revenue stratum within urban locality. Deslatte and Swann [65] examine whether cities with higher social imbalance embrace green building practices less intermittently compared to cities with less social imbalance and find that regional income inequality dampens the factors that stimulate policy adoptions. Theme III will examine energy efficiency, land use, climate change, and inequality to environmental and social factors together to model the diffusion at multiple scales of green policy tools, which are generally aimed at spurring private investment in green

infrastructure. Green building investment has been linked to environmental, energy and human health concerns. We employ survey and classical data to examine a range of demographic and socio-environmental drivers of green building policy adoptions by local governments from huge sample of American cities.

Different policy initiatives have been undertaken by provincial authorities to boost sustainable building methods, which include LCA for systematically investigating the environmental impacts of dwellings; stimulus for energy efficiency through high performance design; water conservation and by employing green building codes for certifications such as GreenStar in Australia, Green Home Evaluation Manual (GHEM) in China, or Leadership in Energy & Environmental Design (LEED) in the United States [66,67]. Provincial authorities implement sustainable building methods using unique mechanisms like: energy assessments of houses and business; stimulus for HVAC upgrades and renewable energy (solar/wind), low-energy appliances; compulsion for new and retrofitted construction to be LEED or Energy Star certified; authorizing ultra-dense expansion near public transit junctions; lowering tariffs on eco-friendly expansion and stimulus for mixed-use growth. Research on the diffusion of such tools at the sub-national level has often grouped tools into additive indices in order to assess an overall level of "sustainability" of cities, although this methodology is not without its flaws [65].

The information of this theme needs outcomes of Theme I; and the results of Theme III will be utilized as input data for Theme II and IV. This theme provides a new direction for Theme V. Further, we utilize interdependence of Themes II and III since the understanding of human behavior is essential to successful policies, and aspects of individual decision-making are uncovered by specific policy designs and mechanisms.

The policy instruments to pursue SHBE may at times conflict or crowd each other out, rather than complement each other [68]. Noailly [69] study the impact of environmental policy on innovations pertaining to technologies for improving energy efficiency in buildings. The focus is really on regulatory energy standards in building codes, energy taxes that are reflected by energy prices and R & D spending through clearly identified governmental energy priorities. The innovation in energy efficiency technologies is carefully considered based on eight identified technologies like insulation, high-efficiency boilers, heat and cold distribution, ventilation, solar boilers, energy saving lightings, building materials and climate controls. Although energy prices did not have any significant impact on growth of patent filings, it was observed that tightening of minimum standards for walls by 10% would cause the patent filings to increase by approximately 3%. The authors conclude that in the building sector the tightening of energy policy and regulatory measures would significantly affect innovation

propagation rather than producing any impact on energy prices and R & D support. The ENERGY STAR program, which was introduced by the United States Environment Protection Agency in 1992, is the topic of investigation for Datta and Gulati [70]. The authors analyzed the rebate program for ENERGY STAR products for the whole US. Specific study has been performed for clothes washers, dishwashers and refrigerators. The increase of \$1 for population-weighted rebate results in 0.4% increase in ENERGY STAR qualified clothes washers. These rebate programs have contributed in reducing 5.5×10^4 tons of carbon equivalent while the clothes washer program was found to be very effective, having a positive impact on product adoption by the population. The rebate program for refrigerators and dishwashers did not impress the population much.

Theme III also focuses on identifying the impact of policy on individual level decision-making and its fundamentals such as risk aversion and response to incentives can inform policy design. Research in this topic consists of two independent and complementary directions.

The first is a field experiment with the goal to identify the implications of offering multiple policies to individuals and below is a description of a few ways that the authors will be investigating this phenomenon: One examination into technological implications at the individual level is an analysis of recommendations made by auditors through Tallahassee Utilities. These audits are used to inform decisions to engage in policy actions intended to improve the housing stock characteristics of the home through technological upgrades. The gap between current housing stock characteristics and the technological recommendation made is identified. It identifies the impact of technological sophistication on policy participation. Additional work in this area can examine the impact that policy participation at the local level has on the contribution of producing environmental public goods. This allows for the examination of policy spillover between energy and water consumption at the residential level. The preliminary research suggests that while some energy oriented policy can contribute to water reduction, other policies that focus on technological improvements within buildings may result in an increase in water consumption and a decrease in energy consumption. Therefore, local policies need to be designed with attention to their direct and indirect effects.

The second direction employs mathematical modeling and economic experiments to study the fundamentals of decision making in the environment where pro-environmental decisions create an element of interdependence between users, which may resemble a public good, or a public bad aspect. In addition, similarly to uncertainty present in the field, the environment has strategic and exogenous uncertainty affecting the decisions and incentive structures. Pevnitskaya and Ryvkin [71,72] developed a mathematical model and confirmed by experimental data

that decision makers considered their own profit, efficiency and social preferences when making pro-environmental and own benefit maximizing choice. The authors estimated the magnitude of both effects. Further, they found that when given an option to invest in clean technologies, individuals used it and the effect was enhanced when technology sharing or complementarities were allowed by the mechanism/policy. These results provide foundation for developing models of how SHBE affect the society on a global scale, including energy and water pricing. SHBE will inevitably affect policies about energy market, whether to allow buildings to be off the grid, and how to design efficient markets that include energy submitted to the grid by the users.

2.4 Theme IV—modeling dynamic LCA and business ecosystem

Environmental LCA, a method for estimating environmental impacts, has different definitions. For example, Rebitzer et al. [73] defined that LCA is a systematic scheme of investigation for assessing the environmental impacts which are characteristics of the life cycle of the said product, such as climate change, ozone depletion, tropospheric ozone (smog) creation, eutrophication, toxicological stress on human health and environs, the consumption of assets, water use, land use and noise pollution, etc. In the meantime, the International Organization for Standardization (ISO) 2006 defines LCA as a “compilation and evaluation of the inputs, outputs and the potential environmental impacts of a product system throughout its life cycle” [74]. Additionally, according to the Environmental Protection Agency (EPA), LCA is a “cradle-to-grave” approach for assessing industrial systems [75]. “Cradle-to-grave” begins with the gathering of raw materials from the earth to create the product and ends at the point when all materials are returned to the earth.” These different definitions, however, have something in common, which is the life cycle perspective to determine the environmental burdens of a product, process, or activity.

Recently, the concept of LCA has been evolving from solely focusing on environmental consequences to a broader scope that also include life cycle costing and social LCA [76,77]. The evolution seems natural because the extension of environmental LCA to life cycle sustainability assessment ultimately puts human and economic considerations at the same level of significance with the environmental performance.

In the context of built environment, LCA as an estimating and assessment method has been applied to evaluating the environmental performance of building products, processes and building themselves [78–81]. Especially at the building level, the environmental impact of a building during its lifecycle includes the impact from its occupancy stage, in which human and its behaviors

cannot be ignored from the perspective of building energy consumption [82]. In addition, uncertainties associated with the context of a product, process or building, such as technological progress, can affect the results of an LCA significantly. Such uncertainties are not sufficiently addressed in many LCA studies [83].

The evolution calls for new ideas, methods, and theories to advance the existing LCA framework for integrated building assessment, and develop scientific and operational underpinning to support research in sustainable built environment. While many ongoing dynamic LCA studies are looking into the spatial and temporal dynamic aspects of LCA, there is also a need to consider the impact of human behavior and business decisions on the life cycle of building products, processes and building themselves. Nevertheless, how to effectively address human and business needs and their impact on the natural environment using an integrated assessment framework becomes a new challenge, both in theory and in practice.

Most of classic LCA is static [84]. It has long been recognized that the results of LCA are affected by contextual factors such as industrial and environmental dynamics [85]. Such limitations of the classic LCA have been extensively reported, among which the lack of considerations for spatial variations and temporal factors is a major example [84,86,87].

Temporal factors are associated with environmental dynamics. For example, Levasseur et al. [88] developed a dynamic life cycle inventory with the temporal profile of emissions and used time-dependent characterization factors for a given time horizon to address time sensitive environmental processes. Similarly, Collet et al. [89] developed a methodology to select a process and emission couple, for which the consideration of time was deemed important. This methodology was based on two important concepts, the timescale of emissions and an impact timescale. If the emission scale was short compared to the impact timescale, the dynamic of the emissions was neglected. Otherwise, the time impact of the emissions should be considered.

Spatial variations are associated with many different factors such as land use and industrial activities and environmental impacts over time [90,91]. The focus of this consideration is on characterization factors and location specific modeling [83,92].

Other types of dynamic LCA includes considering technological changes related to the subject of study, indoor environmental quality for human health and productivity metrics [93–95].

Typically, such variations have been addressed as uncertainties in LCA. New dynamic analysis in LCA also received much research attention recently. Stasinopoulos et al. [96] proposed using system dynamics to consider changes over time in resource flows and environmental impacts. Collinge et al. [97] extended the Mutel and Hellweg [98] LCA model to include time-

dependent variable in order to account for temporal variations.

2.5 Theme V — model assimilation and confirmation

The terminal objective of this theme is to analyze advanced modeling procedure, which facilitates compelling assimilation of multidisciplinary information prototypes and meticulous confirmation model performance. This network effort concentrates on investigation of model assimilation procedures, evolved at multidisciplinary interfaces, advancing those procedures in the human-building ecosystem level, and verification system through this nexus pursuit. The justification approach of this theme rests upon investigations based on following limited multidisciplinary synthesis endeavors: ① assimilation of human factor in green building design; ② dynamic life cycle energy information modeling (please refer Theme I and Theme III) (from design to construction to operation); ③ diverse confirmation projects carried under different establishments across the world. Various such buildings have been built at different institutions across the world. Such buildings are designed as test-bed for numerous technologies with large number of sensors installed which collect real-time data for building performance analysis. Examples include Information Technology Enabled Sustainability Test-bed (ITEST) at Carnegie Mellon University, new office buildings at US DOE's National Renewable Energy Laboratory as a test bed, and the Zero Energy Research Laboratory at the University of North Texas.

Lam et al. [99] integrated data mining techniques in order to find OB with EnergyPlus model for energy modeling of Phipps Center for Sustainable Landscapes (CSL) in Pittsburgh, Pennsylvania. It is a 2-story 2262 m² building. The authors used Fitbit Flex Plugwise smart meters for collecting individual office appliance data and later developed and tested candidate algorithms like support vector regression (SVR), linear regression (LR) and locally weighed learning (LWL) for creating occupancy schedule. The EnergyPlus model was calibrated on systematic basis by replacing TMY 2013-type weather file with the actual weather file of Pittsburgh and then subsequently feeding the real occupancy schedule. The interior and exterior lighting schedules were developed by inverse calibration method and then HVAC parameters were calibrated. The model of Lam et al. shows mean bias error (MBE) ranging between 1.27% for total annual energy use intensity (EUI). The Stochastic Model Predictive Control (SMPC) was developed by Oldewurtel, et al. [100] and deployed on selected sites in Europe and it outperformed current practice. SMPC is a strategy for controlling indoor conditions in a building by considering weather uncertainties. SMPC was found to be more effective in predicting non-renewable primary energy (NRPE) usage and thermal comfort when compared to RBC, which is current control practice. The SMPC is also

effective in predicting smaller diurnal temperature variations. The authors conclude that SMPC can prove to be a promising approach for controlling indoor conditions in buildings (Ramesh et al. [101] developed a unique energy information model for a 28-acre urban neighborhood in Pittsburgh, Pennsylvania. The data are visualized using Geographical Information Systems (GIS). The energy simulation of mixed use 28-acre urban neighborhood was developed using DesignBuilder/EnergyPlus and ASHRAE 90.1-2010 Appendix G (Performance Rating Method) baseline input parameters and the output of this model was represented on the GIS. The integration of energy simulation and GIS helped in visualizing and monitoring entire site energy consumption and EUI. C4.5 algorithm was deployed to understand the pattern of appliance electricity consumption in an office building Intelligent Workplace (IW) at Carnegie Mellon University in Pittsburgh, Pennsylvania by Zhao et al. [102]. The authors used LR algorithm to predict the occupancy schedule. The two algorithms (C4.5 and LR) were integrated to provide OB and the schedules of their usage. OB of 6 office workers was divided into occupied computer-based work, occupied non-computer-based work, remote computer-based work, and unoccupied. The algorithms can predict and recognize individual OB with an accuracy of 92.39% with a coefficient of occupancy schedule prediction of 0.92.

A novel approach is utilized by integrating BIM tool Revit with daylighting simulation tools Radiance and DAYSIM. Since translating Revit data into Radiance is very tedious along with the requirement to manually add input parameters for the creation of complete Radiance input files, a seamless connectivity between Revit, Radiance and DAYSIM was ultimately necessary. This integrated model was tested on a sample building. The BIM-generated Radiance model was able to create human-sensitive daylighting image, false color image and iso-lux image of the Stanford University 2013 Solar Decathlon House. The method was successfully validated through further improvements with the integration of thermal and daylighting analysis along with multi-objective design optimization are possible [103].

Lasternas et al. [104] found that EUI is not the best way to assess OB impact on energy use. New energy metrics called Metrics of Sustainability which integrate company policy and OB of office workers were developed. Prentow et al. [105] developed methods to detect commonly used routes inside the buildings. The method has overcome challenges of great variation among path density and positioning accuracy inside the buildings. The InTraRoute method developed by authors could be used for building navigation and route prediction for facility management and maintenance scheduling in huge buildings. Ruiz-Ruiz et al. [28] developed a novel technique to predict population density inside large buildings by utilizing Wi-Fi network. To remove disturbances created by nearby

noises and to refine and detect various amount of devices which are inside the building and outside the premises, they utilized machine learning techniques and rule-based labeling method. The authors successfully detected the population behavior and detected 95% of the signal received with complete accuracy and full fidelity with noise removal. Due to privacy reasons, it was difficult to gather complete ground truth data, but the authors claim that their methods are reliable and useful in predicting flow of people per area and classification of behavioral roles of people inside the building. Spiegelhalter and Vassigh [106] developed a new learning tool and environment for teaching students, architects, engineers and etc. about “Achieving Best Practice Net-Zero Energy Building Design Instruction Methods.” The authors performed experiments from 2009 to 2012 by studying the effectiveness of this new software tool and animation DVD about net-zero energy building and other building features, materials, life-cycle analysis and passive heating/cooling systems from two universities Florida International University (FIU) and State University at Buffalo (UB). The authors conclude that software tool and animation DVD produced significant improvement in student understanding of net-zero energy building designs and technical knowhow compared to conventional textbooks. Spiegelhalter [107] has studied the retrofitting and transformation of 9246 m² Paul L. Cejas School of Architecture at FIU. The author has utilized building management software Metasys from Johnson Controls. For analyzing different energy efficiency scenarios the authors utilized Autodesk REVIT MEP and for energy modeling eQUEST and Green Building Studio Cloud Software. Since the Metasys system did not record light intensity and outdoor weather conditions, MONNITM and HOBOTM, a secondary wireless sensor system was implemented to get those data at multiple points in the room and outside. The authors conclude that such a retrofitting, usage, and implementation of energy efficient technique can reduce the university electricity bill by 30%.

3 Current challenges and future directions

3.1 Future research directions

OB has its own stochastic and complex nature. This complexity presents us with methodological and theoretical limitations. Because of these limitations, behavior interventions have not been systematically designed, applied and analyzed. Studies with data regarding CO₂ reduction due to behavioral changes of occupants require a deeper investigation. Along with systematic evaluation of interventions, there is also a need for analysis of determinants, which lead to specific energy-related behaviors. It also remains to be evaluated that what would be anticipated effects targeted energy-related

behaviors and their consequences. Clothing adjustment studies and air-conditioning operation studies still need to be evaluated and reliable and accurate data has not been presented yet in the literature [10]. In addition, occupancy detection has remained a challenge and no study with reliable recommendation for probable candidate in terms of sensors for occupancy detection has been presented.

Though lighting energy related behavior studies have been presented in literature, there is a major gap in the area of water usage behavior. Another major area of focus is Venetian Blind slat angle measurement. Due to the highly sensitive nature of daylight transmission, the sensitivity of transmission can be dependent on slat angle and blind slope position. There is also less knowledge about how inhabitants behave with regard to partially open or closed windows. Studies pertaining to opening and closing of doors for adaptive comfort of inhabitants remain to be performed. Understanding with regard to midday clothing adjustments, has not been presented in current literature and further exploration is necessary. Studies consisting of high dynamic range (HDR) cameras for measuring glare in a cost effective, less complex manner remains to be evaluated. Quantitative analysis of window and door opening/closing operating behavior needs to be evaluated.

Confusion still exists in using occupancy models in laboratory settings because they usually do not represent the reality. The challenges related to laboratory-based models are paucity of continuity and natural working environment. Social constraints and dynamics, familiarity with environment and applicable adaptive behaviors remain challenges in creating realistic occupancy models. Contextual factors that are reported by scientists although rigorously analyzed, they are always undervalued pertaining to their effect on occupancy behaviors. A consistent methodology for reporting contextual factors is the need of the time. In addition, it is very essential to identify irrelevant contextual factors; this will help to reduce time consumed in collecting huge data sets. The effectiveness of multi-behavior models is unclear. Two behaviors can achieve same goal (e.g. during summer, removing a piece of clothing or turning on the fan both can achieve goal of cooling the occupant). More studies should be performed with multi-behavior modeling. Effectiveness of multi-year studies also needs to be evaluated. Collecting adequate data sets and sample size equivalent to represent population of required size are of paramount importance. Creating realistic OB patterns based on large sample size, which will be representative of target population and based on survey from various climates, is the need of the hour. Studies focusing on all varieties of building types and building technologies with pilot testing on real building and retrofitting projects should be performed [108,109]. Occupant movement schedules need further refinement by developing more accurate meeting event model with consideration to personal absent days. Such models need to be extended to residential buildings [110,111]. Experi-

mental studies focusing on new and innovation observation techniques for analyzing human-building interaction and measure its impact on building behavior in terms of energy. Development of new frameworks focusing on specific behavioral interventions or energy policy into the BEM needs to be accomplished yet. Integration of social science insights and promoting such methods to enhance amalgamation of BEM with Social Science frameworks is yet to be fully accomplished and efforts that are more concerted should be focused in developing such methodologies [11].

In current building science field, disagreement exists among experts on which information to collect, which variables to observe and with which sensor and what should be the accuracy of those, what should be the length of time step and what should be the duration of observation period. The area of building science is experiencing dearth of consistent methodology in methods, models and simulations; scientific community today needs improved and realistic behavioral models to mimic natural environment and meet experts' criteria. The accuracy of statistical model will be improved by developing schedules for going-to-work and off-work periods. Additional models need to verify for weekends for lighting energy [24]. The current model implements traditional interventions like peer-pressure and discrete interventions, but game based methods and incentive-based techniques should be studied in the future. Predictive variability of the model should also be studied related to human behavior which requires huge data [25]. Overcoming lack of personalization in statistical methods along with improving the behavioral patterns through driver-response conditioning and motivational factors in relation to window opening data mining can bridge the performance gap [26]. Challenges remain in connotation of detected movement patterns with respect to the built environment and social and cultural differences [27]. The effect of specific factors like operating hours, number of occupants, and use of space like mixed use, commercial cooking, data centers, etc. should be investigated in future. Less data are available for such analysis [42]. Artificial neural networks (ANNs) should be implemented and investigated in multiple multi-family residential buildings. Implementation of feature selection techniques like "The Lasso" also needs serious investigation for performance with energy modeling software [33].

Looking at human-building ecosystem in relevant constraints of broader "business ecosystem," other factors which make this concept applicable and commercially achievable and relevant for its neighborhood, state and federal commission and natural ecosystem should be included. Procurement of construction materials, physical systems and appliances and their tariffs and rewards decide the position of human-building ecosystem relative to other existing systems. So, critical determination of ecosystem optimization must be based on variables both within human-building ecosystem and among the human building

ecosystems and other systems prevailing surrounding it.

Under such a context, future research in LCA should address the following questions:

- 1) What are the new opportunities brought by considering the “human” dimension in LCA of buildings?
- 2) What is the impact of the new “human” dimension on the existing LCA framework? What are the advantages and disadvantages?
- 3) How are “business ecosystems” connected with the life cycle thinking of buildings?
- 4) What are the missing pieces in the existing LCA framework that would help us to incorporate the human and business dimensions?

3.2 How data can be collected?

Data can be collected through a number of methods, such as surveys, interviews, laboratory experiments, computer simulations, and case studies. Surveys provide valuable information regarding current human behavior, attitudes, values, and perceptions, and allow for feedback regarding what changes people might be receptive to. Some information, such as thermal comfort, cannot be measured directly by an experiment since it is subjective, so surveys provide an opportunity to learn such perceptions. Laboratory experiments and computer simulations can measure the performance of equipment, building design, as well as test new variables before conducting a case study. Case studies are perhaps the most informational method of gathering data since they provide information regarding what happens in a real-life environment. Table 4 identifies types of data collection methods found in literature.

3.3 Data structure

The observatory, called SOPHI (System for the Observation of Populous Heterogeneous Information), federates/shares both data and analytical tools. SOPHI is developed and operated by the Data Science Initiative (DSI) and the College of Computing and Informatics at UNC Charlotte. DSI is a multidisciplinary initiative whose objectives are to facilitate and sustain research and academic activities among centers of expertise in data collection, curation, analytics, and visualization across a broad range of

research domains. DSI is enabling research collaborations across all elements of the university and with external collaborators from both the public and private sectors. RCN inspired research to understand human behavior to promote sustainable building-scale ecosystems is often a data analytics intensive activity. As such, SOPHI is expected to become an important asset (both for its data sets and for analytical toolkit) to RCN members.

SOPHI, as a cornerstone of DSI, embraces a mission that promotes and enables the management and efficient use of “big data” and “advanced analytics.” To fulfill this mission, SOPHI provides a scalable data management infrastructure coupled with a consolidated user experience that enables access to a rich suite of analytic tools, computational engines – e.g., HADOOP – and diverse, disparate data sets. Coupled with its backend data handling, computational engines, and analytic features, SOPHI’s Graphical User Interface (GUI) serves as an intuitive, user-friendly portal through which data scientists – and those domain experts whose expertise may not include familiarity with the intricacies of code and command-line driven operations – can generate useful insights from varied, voluminous, diverse data sets.

SOPHI offers a high degree of protection for proprietary or sensitive information. Data security and governance were central concepts during the earliest planning and design stages for the observatory. Central to this is a rigorous, standardized data governance regimen. The observatory’s governance structure controls access to data and tools so that raw data holdings as well as the results of analytic activities can be accessed as needed from tightly controlled to freely available. This capability removes a significant overhead and burden from the shoulders of individual researchers to ensure the proper handling of multiple, diverse data sets, each of which may have its own unique handling and security requirements.

The architectural framework for SOPHI is depicted in Fig. 2. This framework overviews key features and illustrates SOPHI federation with external, remote data stores. This functionality provides researchers with a seamless access capability to utilize data sets and tools outside of the immediate SOPHI environment. SOPHI reached a limited Initial Operating Capability (IOC) in May 2015 that links data and analytics at UNC Charlotte

Table 4 Methods of data collection in literature

Data collection method	References
Survey	[18,53]
Social media	[34]
Experiments	[3,5,15,17,31,37,40,42,46,47,49,53]
Simulations (data mining, machine learning, parametric modeling, building energy simulation, etc.)	[5,6,8,9,22,25,26,29,30,32,34,35,38–43,45,47,48,53,54]
Sensors	[27,31,33,37]
Wifi/network analysis	[15,28]

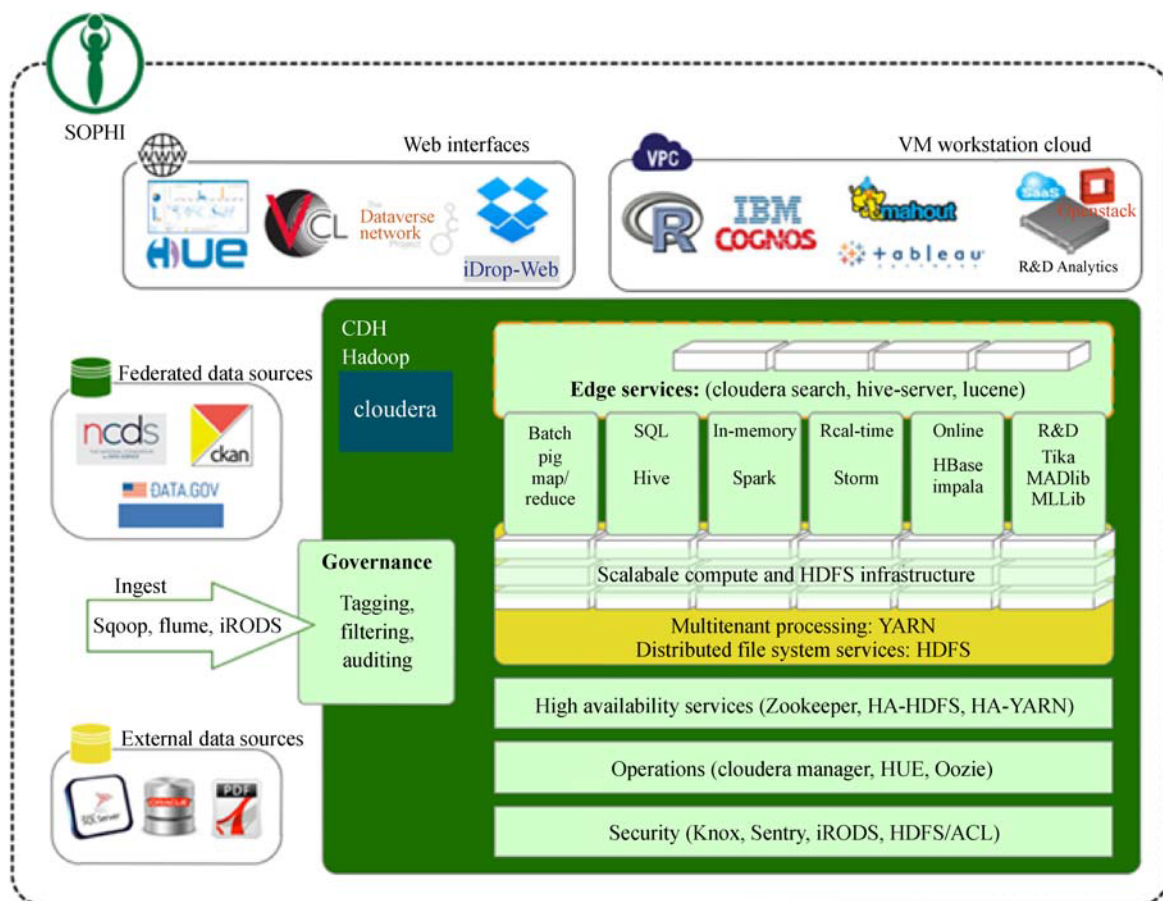


Fig. 2 SOPHI architecture

with those at North Carolina State University and the Renaissance Computing Institute at UNC Chapel Hill. Enhancements to SOPHI are continuing toward the release of a Full Operational Capability (FOC) slated for May 2017. Features and capabilities will continue to be added to SOPHI beyond these milestones through future releases. In particular, SOPHI is developing a data ingest capability to allow data providers to upload data sets, both structured and unstructured, to the observatory. The ingest capability will operate under SOPHI's governance protocols and support the generation of metadata to ensure that the observatory's data catalog is complete and current [112].

As information is gathered, it feeds into the data structure shown in Fig. 3. Case studies, white papers, and the gathering of data can be contributed to the research collaboration platform through SOPHI. This fosters effective collaboration among researchers of individual fields, which may synthesize the shared information to create a better understanding of SHBEs as a whole. Therefore, Fig. 3 explains the proposed data structure in visual manner. Figure 3 explains that the proposed data structure will be a 3-tier format and in this structure the first tier will be focused on either individual building or community level. In addition, the impact of sustainable

policies will form first tier. The second tier consists of "data" to be collected and "case studies" which will be studied or have been studied already. The third tier includes expansion of second tier components. This means that for example consider second tier component "data"; the third tier will included expanding the "data" component by adding types of data, which will be considered for investigation. Similarly, for "case studies" component, the third tier will mean identifying the case studies currently under study or in future consideration or already concluded investigation. Consider, for example, the first tier component "individual building." Here, the second tier components for "individual building" are "data" and "case studies." Now for second tier component "data," we have identified the types of data to be investigated as "materials," "comfort," "weather data," "design," "water" "occupancy," etc. these components form third tier for "data." Similarly, third tier will be added for "case studies" once such cases are identified. This tier structure can be further expanded based on the data types identified. For example, "materials" can be further expanded as to "steel," "polymer," "glass," etc. This data structure is a starting point in identifying and reporting the types of data to be collected and investigated. Furthermore,

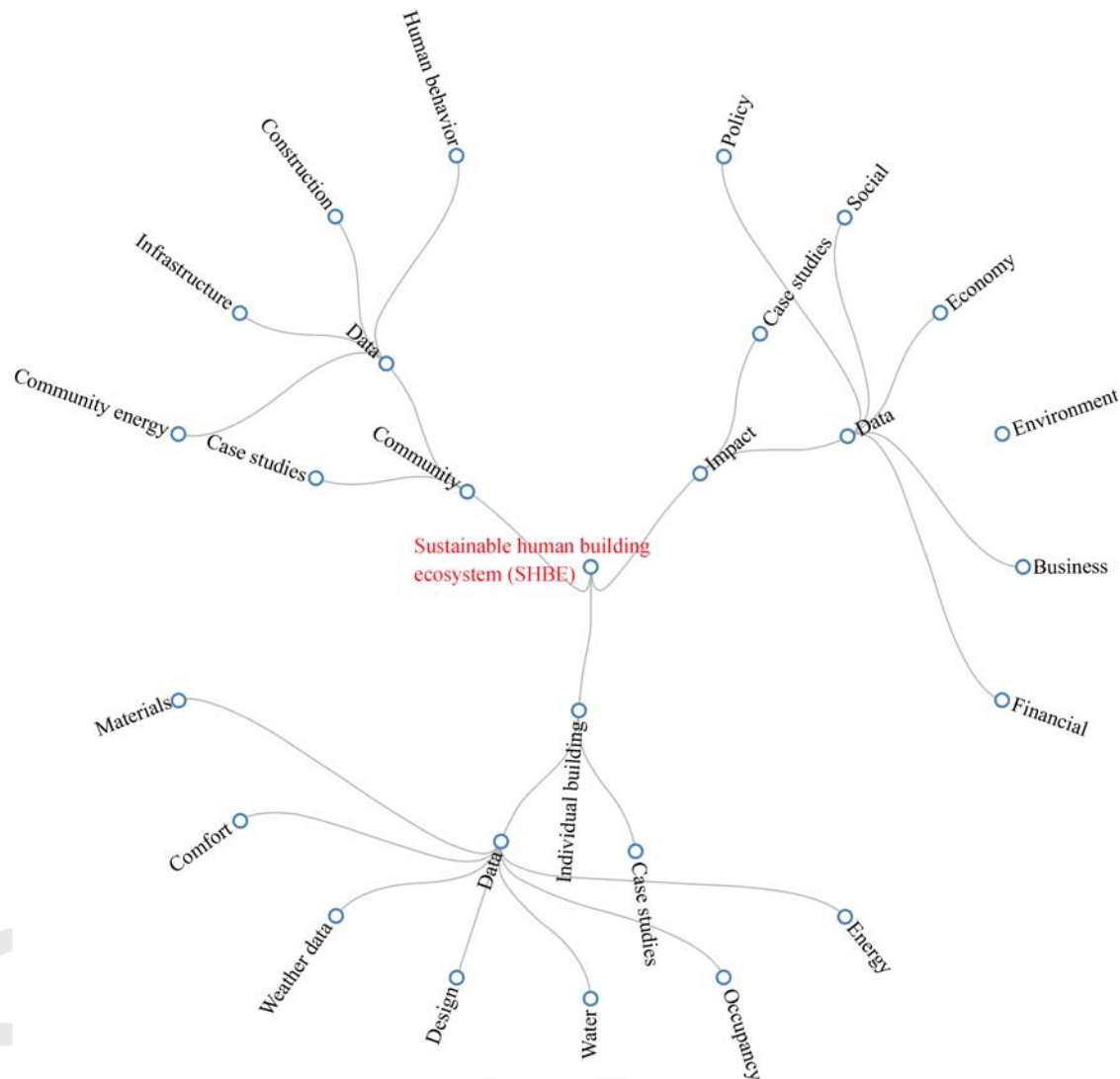


Fig. 3 The proposed data structure for compiling data

a consensus-based data sharing mechanism can be developed.

4 Conclusions

A growing number of research has been focused on the field of sustainable human-building ecosystems, yet, a deeper and compressive work with an interdisciplinary perspective require more attention from the community. As research continues, improvements are being made such as new technologies, better modeling, and more informed policy-making. The goal is not just to develop new energy-saving ideas or technology but also to learn about the process of increasing sustainability, so that efficiency is increased in the future on both the research side and the implementation to society side. This requires a collaborative effort of minds from various disciplines such as

engineering, software design, sociology, and law. As discussed in Section 3 about future research directions and proposed data structure, those suggested actions could potentially tackle the complexities involved. With this in mind, the SHBE-RCN is working toward a better understanding of what will be beneficial both to individuals and to society as a whole.

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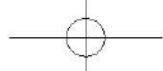
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Energy modeling and data structure framework for Sustainable Human-Building Ecosystems (SHBE) —a review

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Frontiers in Energy

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