GAME ENGINES AS A PERFORMANCE-AWARE PARTICIPATORY AND INTERACTIVE DESIGN PLATFORM: A PROTOTYPICAL WORKFLOW

Arman Khalilbeigi Khameneh
Alicia Nahmad Vazquez

University of Calgary, SAPL
Calgary, CANADA
{arman.khalilbeigikha, alicia.nahmadvazquez}@ucalgary.ca

ABSTRACT

This paper explores human-building interaction as an active factor in the early stages of the design process. Current design methods allow a range of highly sophisticated tools to measure and analyze quantitative design parameters such as structural, thermal, lighting performance and more. However, interpreting human preferences and occupant behaviour as metrics to inform early design stages remains largely unexplored. Game engines' are examined for their capacity to steer the design process and embed performance data. Furthermore, the virtual environments they enable are investigated qualitatively and quantitatively as tools for engaging with user preferences. The resultant metrics are then exported into architectural design software to be used as tools by the designer. Finally, the present context in which game engines are applied in architectural design is examined. The paper proposes a framework that enables non-designers to participate in a data-driven, performance-aware participatory environment actively is created and ready for data collection. Components of the platform include direct and indirect user feedback that enable designers to understand user preferences and quantify its qualitative features. Finally, a case study is presented using the developed platform to design high-performance facade panels.

Keywords: participatory design, game engines, user-informed design, occupant behaviour simulation, spatial occupancy.

1 BACKGROUND: HUMAN-BUILDING INTERACTION

Human-building interactions and occupant behaviour have received much attention in the literature due to recent advances in computer modelling, simulation tools, and analysis techniques, which aim to improve building design processes and operation strategies. (Azar et al., 2020). Building occupancy is essential for building performance simulation, but it is hard to represent due to its temporal and spatial stochastic nature (Wang, Yan, and Jiang 2011). According to these studies, occupant behaviour is related to more than just the presence or absence of people in buildings. However, defining this human component, a multidimensional factor that necessitates a fundamental understanding of the geographical, temporal, and social elements of human decisions, can be challenging. Understanding building occupants' spatial and temporal activity patterns, user dynamics, and the socio-technical intricacies of occupant behaviour is complex (Shen, Newsham, and Gunay, 2017; Sonta, Simmons, and Jain, 2018).

1.1 User Participation and Assessment

It is well-acknowledged that occupancy factors strongly affect a building's performance (Saeidi et al., 2018). Occupants actively contribute to their built environment, influencing its performance and quality (Azar et al., 2020). The lion's share of the literature has focused on occupant behaviour's impact on energy balance and consumption (Nord et al. 2018). Beyond energy consumption, however, inhabitants' behaviour affects virtually every aspect of a building's lifecycle. It is well established in the literature that user behaviour is the main source of uncertainty in building performance analyses. (Nord et al., 2018; Sonta, Simmons, and Jain, 2018; Jia, Srinivasan, and Raheem, 2017; de Wilde, 2014). On the other hand, current occupant assessment techniques do not explicitly consider occupant dynamics in their implementation (Sonta et al. 2018), limiting their ability to uncover insightful information about activity patterns in the outcome.

Current occupant activity simulation techniques rely on simulation models developed from data collected using costly methods such as 1) formulating heuristics from previous cases and predetermined patterns and 2) capturing occupant behaviour from sensory data. In a recent comprehensive study, Azar and O'Brian (2020) conclude that such tools treat occupants in simplistic ways that fail to recognize their stochastic, diverse, and reactive nature, affecting the quality of their estimates. Similarly, other agent-based studies erroneously equated presence with action or event occurrence, assuming that an agent will always perform the same actions regardless of changes in the environment or itself (B. Lee et al. 2021).

Numerous interconnected factors influence human behaviour. Such as physiological and physical factors (Kanthila et al. 2021; Yan et al. 2017). Further, the occupants' psychological condition, location, type of building, climate, social and cultural status and background all impact their choices. Influencing factors can be categorized into three groups (Shen et al. 2017): Temporal (time-bound), Spatial (tied to space and built environment), and Personal (related to physics and psyche). It is critical to close the gap between predicted and actual human performance for buildings to be adaptable to change and maintain good performance over their lifetimes. These studies acknowledge the lack of a systematic approach to studying occupant behaviour in depth, which requires further investigation. As a result, the *"predicted or analyzed"* and *"actual"* are significantly different. Understanding end-user behaviour beyond the predefined static methods is thus crucial.

Incorporating human-centred knowledge into the design process can help to close the gap between simulation and reality. According to Tabak and de Vries (2010), individuals are too random to completely model occupant behaviour. As a result, real-time data is required to solve this problem (Tabak and de Vries 2010). The field of occupant interaction assessment is new, and there is a lack of observational and empirical data. Furthermore, various physiological, psychological, and sociocultural factors must be considered when using behavioural models, and many potential influencing factors have yet to be discovered (Yan et al. 2017). Recognizing the deficiencies in modelling methodologies discussed above has aided in developing user behaviour modelling tools and methods that seek to fill some of the gaps. Attempts at integration can also be seen in holistic modelling frameworks, including performance analytical tools with user assessment capabilities (Azar et al. 2020). However, most studies concentrate on post-occupancy or building operations rather than design strategies covering a constrained range of building performance variables (such as light control and HVAC systems). Even though these studies are crucial for understanding how to operate current structures, it can be challenging to generalize the findings and apply them to new designs or other structures (Saeidi et al., 2018).

It can be concluded that: 1) the design process of actual buildings cannot be effectively scaled or deployed using current approaches (Azar et al. 2020; Sonta, Simmons, and Jain 2018; Jia, Srinivasan, and Raheem 2017); 2)Including end users in the design process, whether in post-design evaluation and optimization or in the early pre-construction design stage, is difficult due to the complexity of human behaviour and preferences. Hence, moving away from post-occupancy data extraction for feeding into design tools toward the earlier integration of real-time user information is of great importance.

1.2 Current Methods of Evaluating User Preferences

Design methods incorporating user preferences into the design outcome are broadly classified into simulation-based methods, artificial intelligence (AI), or machine learning techniques (ML). Agent-based modelling or multi-agent systems, statistical analysis, and stochastic modelling are the four categories of data-driven simulation-based or rule-based techniques (Jia et al.). (2017). Recent research has attempted to use AI and ML methods to obtain more predictive means of user evaluation. Markov Chains, Multivariant Gaussian models, semi-Markov models, Linear regression, State vector regression (SVR), Artificial Neural Networks, K Means Clustering, and K-Nearest Neighbor are some commonly used methods in this field (kNN) (Peng et al. 2018; Khosrowpour, Gulbinas, and Taylor 2016; Li and Yao 2020; Lee, Tong, and Cheng 2014; Dong and Lam 2011; Dong and Andrews n.d.; Erickson, Carreira-Perpiñán, and Cerpa 2011; Chen, Luo, and Hong 2016; Sonta, Simmons, and Jain 2018).

Based on the authors' reports for both approaches, stochastic modelling and ML methods based on ground data can better track long-term occupant presence/absence status patterns. Agent-based modelling, on the other hand, has a greater potential for combining occupant behaviour models with simulation and design tools. Stochastic models can be scaled up for real-time modelling. According to Azar et al. (2020), object-oriented agent-based models are the largest subsidiary capable of adapting to different model sizes and complexities. The critical point is that this tabulation overlooked the newly emerging field of performance-aware design systems in non-semi- or full-immersive and game engines.

A critical analysis of current approaches to user assessment and means to gather reliable information about user preferences identifies four key shortcomings. First, the present design tools do not adequately capture the enormous complexity of individuals. Second, the use of simplified simulations rather than accurate ground data is the cause of the discrepancy between the simulated and actual results. Third, a comprehensive data-driven strategy that considers various building performance factors and user preferences is lacking. Fourth, there is a dearth of research on the design process itself because most of the literature in the field of user study and participation focuses either on the pre-design or post-occupancy stages. This paper proposes that a collaborative design platform enabled by game engines can be a possible solution to address the deficiencies above.

2 GAME ENGINES IN THE ARCHITECTURAL DESIGN ECOSYSTEM

The recent arrival of game engines into the domain of architectural design demonstrates their potential to be used as an extended design platform with new functionalities. Game engines in building engineering allow various types of data to be integrated into these platforms with an interactive experience tailored to each stakeholder. Due to their interactive data capabilities, they may be effective tools for involving and instructing non-expert and assisting designers.

Game environments and corresponding software platforms offer enhanced graphics, scenario-based design, character design, and embedded artificial intelligence. Whilst building information modelling (BIM) is a collaborative method that facilitates data exchange and management between different disciplines. An increasing amount of information is required for complex and dynamic projects within the architecture, engineering, and construction (AEC) industry. Scholarly publications from 2006-2016 demonstrate this focus and trend. Eiris and Gheisari (2017) grouped the results of AEC publications into: simulation, education, training, and visualization categories according to their purpose (Eiris and Gheisari 2017), concluding that collaboration and communication are among the most studied aspects of integrating immersive technologies in the construction industry. Previously, researchers combined building information data with game engines. Results indicate that the variability in game engine features, such as providing different layers and scenarios, as well as a variety of points of view, aids in a better understanding of building information and improved collaboration in the design and construction fields (W. Yan, Culp, and Graf 2011; Du et al. 2018).

Further experiments involve synchronizing data during changes in the model and elevating the environment to provide an immersive experience. As a result, immersive environments are said to be conducive to involving building users in creative innovation processes together with building designers, as well as for capturing and formulating end-user needs and requirements regarding buildings and their functionality (Edwards, Li, and Wang 2015; Christiansson et al. 2011; Shiratuddin and Thabet 2011). Through collaboration within immersive environments, everyone involved in the design process can access information about the design and can iteratively influence the design from early on. Additionally, procedural modelling in game engines offers data-driven capabilities and emergent or unpredictable complexity. They often result in synergistic interactions with immersive environments that take advantage of their ability to handle dynamic forms, rule-based paradigms, and real-time data flow (Lin and Hsu 2017).

One of the most beneficial aspects of game engines is that they can simulate rules and limitations during the design process (Chien 2002). Using game engines has many advantages in design processes, including the cyclical nature of play, immersive experience, resemblance to workplace situations, higher level of engagement, the ability to provide multiple levels of feedback, and the multiplayer or supervised aspect of gameplay. In any design process, various parameters interact simultaneously and sometimes contrastingly. Hence, a gaming environment offers an excellent opportunity for participants to explore the superimposition of the forces. Additionally, the embodiment aspect of the gamified experience, which occurs through more thorough three-dimensional navigation coupled with annotated data, leads to a more comprehensive understanding of the design subject (Woodbury, Shannon, and Radford 2001). As a result, game engines offer a variety of benefits not just to users with no design background but also to professionals throughout various disciplines who want to gain a deeper understanding of the design process.

3 VIRTUAL IMMERSIVE ENVIRONMENTS POWERED BY GAME ENGINES AS NOVEL EXPERIMENTAL DECISION-MAKING PLATFORMS

Today, distributed communication among people is possible due to the information infrastructure and the average users' access to comparatively high processing power in personal computers or other devices. In many instances, the collective behaviour that results from this widespread digital interaction is a reliable source for problem-solving. For example, Phylo, a multiple game, is one of the most powerful tools available today for studying the evolution and function of DNA, RNA, and protein sequences. InnoCentive is an Open Innovation Marketplace that connects corporations looking for solutions to major problems with a diverse network of people. InnoCentive reports an 80% success rate in discovering a solution (Kwak et al. 2013; Wazoku n.d.). Fort-McMoney is an example of user involvement at the forefront of the city-building decision-making process in a gamified and interactive environment (Dufresne, 2022).

User intervention needs to be coupled with automated computational design tools. "Having no outside agency intervene is a fundamental idea to make possible emergence of this collective wisdom. In other words, judgment depends on the accumulation of the experienced consequences of choices made in complex situations" (Nelson and Stolterman 2014). The process of this collective endeavour is equally important just as the outcome. Not only does it give people voices and realization of possible alternatives, but it also enables them to negotiate the values that are important to them. *"It empowers stakeholders and allows them to feel connected to the design process …[it] is about negotiating values realized through participation. Values in the design process are seen as an ethos that respects people's democratic rights in that the people whose activity and experiences will ultimately be affected most directly by a design outcome ought to have a substantive say in what that outcome is"* (Iversen, Halskov, and Leong 2010). The complexity resulting from synergistic user interactions can be realized only with careful moderation.

Game engines allow us to explore a design system that enables us to capture the diversity and complexity of people as end-users. Using game engines in design is a collaborative venture. In the design domain, games -also referred to as serious games- are engaging, participative, interactive, performance-aware processes. The designer remains at the centre of the design process, creating the environment, establishing design schemes, considering technological limitations, incorporating them into features and rules, creating various scenarios, and enabling user preferences in the form of interactions to be embodied into the design product.

It is significant to note that the authors' approach fundamentally differs from efforts like WikiHouse or BarCode housing in terms of pre-engineering or integrating technical data into the design process (Parvin 2013; Madrazo, Sicilia, and Cojo 2009). WikiHouse offers a great foundation for open-source housing, and the system provides options for layouts, but the participant is still choosing rather than designing. BarCode fills this gap by giving participants graphs tools to employ, and then automatically created algorithms create the design. The participant is not fully involved in the design process in either case. The spatial cognition of those mediums is different from how non-designers perceive spaces. Furthermore, during the process, they are not informed of the performance or consequences of their choices. These two factors, "Augmenting users' perception" (of design) and "informing their decision", are the main elements shaping the proposed framework.

4 PROPOSED WORKFLOW: OVERVIEW

The phrase "user-centred" or "occupant-centric" in this paper refers to including end-users as engaged members of the design process. The suggested approach focuses on the early stages of design and involves non-expert individuals who will be the building occupants. Users are evaluated, directly and indirectly, constantly interacting with the performance-aware environment as they are the primary agency taking control of the design. Also, immersive virtual environments in this context are used in their broader meaning and are not necessarily referring to virtual, augmented, or mixed reality mediums. Studies indicate that regardless of the tool or medium of participation (whether it's a head-mounted display, a projection, or a screen), the primary factor affecting levels of presence, believability, and perception is the content of the simulation (Schwind et al. 2019; Baus et al. 2011; Baños et al. 2005). Therefore, in the context of this paper, '*immersive'* refers to a photo-realistic physical environment developed using game engines that are augmented with information and interaction tools and are similar to the spatial experience of real-world situations. The medium for this study is personal computers and conventional screens.

Studies in spatial cognition and computation have investigated qualitative spatial representation and reasoning techniques in light of how humans abstract from geometrical details when interacting with spatial information. Participants can (and prefer) think about and communicate using qualitative relations when solving various product design problems, particularly during earlier design stages. This mode of engaging with the design process contrasts with exact numerical values, which is common in today's design tools (Schultz, Bhatt, and Borrmann 2017). Further, early design choices determine up to 70% of the product's production cost. Optimizing manufacturing parameters can only address 30% of those (Kleban et al. 2001). Therefore, it can be concluded that the early design stages provide the most significant opportunity for a collaborative, data-driven intervention.

4.1 Technical Framework

A design workflow using a game engine is proposed and developed. Unreal Engine (Epic Games 2021) is the host environment for this workflow. Tools for structural and environmental design compatible with Rhinoceros (Robert McNeel & Associates 2020) are utilized to provide analytical data. Geometrical constraints also can be modelled algorithmically within Rhino's visual programming environment Grasshopper™. Other pipeline elements are coded in Python 2.7 and its implementation for the .NET framework IronPython (IronPython Contributors, Microsoft Corporation, and Python Software Foundation 2013; Python Software Foundation 2010).

Making fundamental changes throughout the design is one of the issues in game engines as they require preparing the majority of the environment features before the game starts. Therefore, making changes during the gameplay is complicated, especially the ones that affect the surroundings. Conversely, design exploration, especially in the early stages, necessitates the ability to create numerous, if not uncountable, options. Therefore, pre-generating all possible design options and bringing them into the game is not feasible. A real-time connection between the host game engine and 3D software capable of performing performance analysis is essential. This connection can be one of the challenging aspects of the workflow. This connection transmits the participant's actions to the analytical section (a Python server with analytical evaluation tools integrated), where information about the performance of that specific alternative or choice is sent back to the engine (Figure 1).

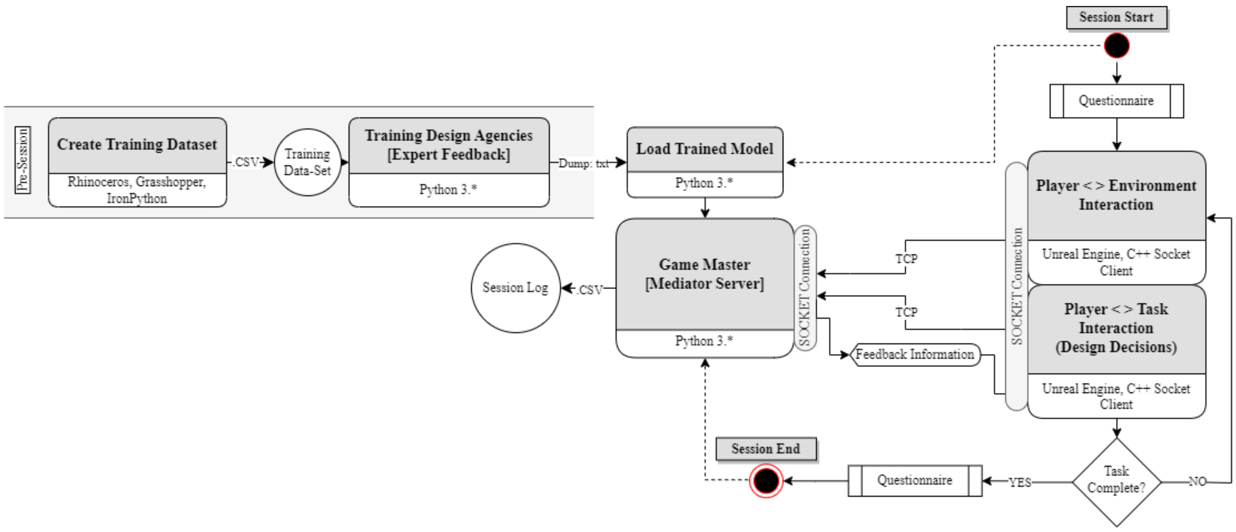


Figure 1: Elements of the developed framework for participatory informed decision-making with connections between the different parts of the platform.

The two-way link between this server and the game engine allows for keeping a complete log of user behaviour and interaction, which is a valuable source of information to research. This connection is essential to the study because the more data is transferred, the more time and resources are allocated, which may lead to inconsistencies in user experiences. There cannot be a noticeable delay in the game session, limiting the time available for performance analysis. This technical limitation is coupled with the fact that entirely accurate analysis is not necessary nor feasible in the early design stages as the geometry and its relation to the surroundings have not yet been fully developed or modelled. As a result, imperfectly accurate but enriched data in the early stages of design can influence the design direction. Similar to a standard method of handling visual details in computational graphics, which depends on how close the viewer is and helps better use system resources, an item is initially obscured. Still, more details are gradually added as the player gets closer or moves forward. Thus, data-driven machine-learning approaches are used to direct design in the early stages. These tools are fast, straightforward, intuitive, and precise enough for the initial design decisions.

The three main types of machine learning are reinforced, unsupervised, and supervised learning. When creating predictive models, supervised learning maps a set of inputs to one or more outputs (the response variable or labels). When the output variables are categorical, supervised learning tasks are described as classification or pattern recognition. Tree-based models are a subcategory of supervised classification methods that use tree topologies to address classification and regression issues. Recent reviews of state-of-the-art techniques for estimating or predicting building performance support that predictive models, like generalized linear regressions, tree-based models, and artificial neural networks, have been widely used in studies to assess various design alternatives. Since they are easy to apply and interpret, comprehendible, and intuitive (H. Sun, Burton, and Huang 2021; Y. Sun, Haghighat, and Fung 2020; Wei et al. 2018). Tree-based AI models are trained to create a data-driven model that retrieves any design iteration's structural and environmental performance.

4.2 Design Evaluation and Conflict Resolution System

Conflict inevitably arises when multiple players can exert power and make decisions on a finite number of elements in a limited space. There may be various approaches to dealing with the problem of contradictory choices. The first approach involves direct unsupervised interaction between participants, allowing people to bargain and negotiate to reach a mutual solution. The second strategy, a supervised negotiation, involves a higher authority meddling and regulating the negotiations because the players might fail or be unwilling to make concessions. This role sometimes is conferred on the platform itself, which needs a ranking or a selection mechanism to solve the conflict. One technique explored to resolve conflicts is implementing a rating or evaluation system based on both performative and qualitative game criteria allowing an upvoting hierarchy that chooses the fittest alternative. When discussing performance, it does not solely refer to environmental, structural, or architectural evaluations and analyses, but several other aspects like desirability or other qualitative variables can and must also be considered. Nonetheless, all these parameters are still part of the evaluation system.

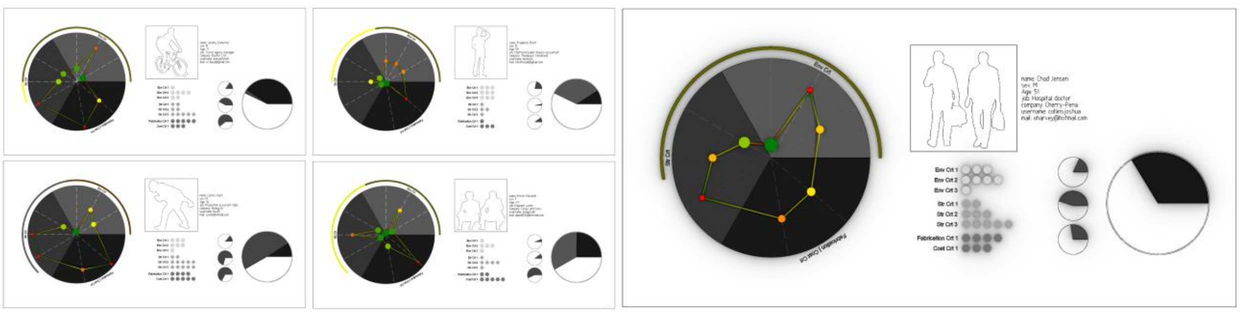


Figure 2: Evaluation system: combining rewards in each criterion for every participant.

In summary, two systems have been deployed to handle various options—a system of rewards and a credit system. The credit system aims to converge options during the game and minimize the generation of outlier data, and the reward system acts after the game to generate the final option. Every participant's final decision in the initial study is recorded with its metadata. The performative variable of each choice is paired with weights in the reward system to give the player an overall score (Figure 2). The credit system uses tokens you can spend per your prior decisions. Extreme deviations will limit players' options in subsequent steps by reducing their token supply.

4.3 Data Collection Procedure and Validation Method

The suggested framework supports both direct and indirect user assessments. Direct user assessments are analyses of questionnaires, surveys, and other explicit data collected from users directly through user interfaces. Indirect evaluation refers to time-binding and event-based studies of the recorded session. For instance, the number of actions/reverts a user performs or the time required for specific activities. Indirect user assessment is one of the significant contributions of the proposed workflow; A thorough factual insight into user preferences is made possible because external biases, especially those related to the observer, such as the Hawthorne effect, are reduced.

Surveys and questionnaires are crucial tools for direct user assessment. They are intended for various purposes that can be grouped into four categories: gathering participant demographic information, familiarizing them with the game's objectives and events, testing the study's central hypothesis, and validating the methodology and results. The Igroup Presence Questionnaire (IPQ), which employs a similar Likert scale, is frequently used by scholars to evaluate software or interfaces' degree of immersion and usability (Schubert, Friedmann, and Regenbrecht, n.d.). Similarly, the Post-Study System Usability Questionnaire (PSSUQ) - a 16-item standardized questionnaire- is also used for human studies (Lewis 2009). The System Usability Scale (SUS) has become a popular questionnaire for assessing perceived usability. SUS is a reliable tool with a reasonably brief questionnaire for measuring usability and has significant reliability (Grier et al. 2013; Brooke 2013; 1996; Lewis 2018). Intel™ created the UMUX (Finstad 2010; Lewis 2018) to obtain a measurement of perceived usability comparable to the SUS but using only four items. Finally, the ITC-Sense of Presence Inventory (ITC-SOPI) test is a similar cross-media presence evaluation tool. It is intended to investigate four aspects: engagement, ecological validity, platform viability, and sense of the space.

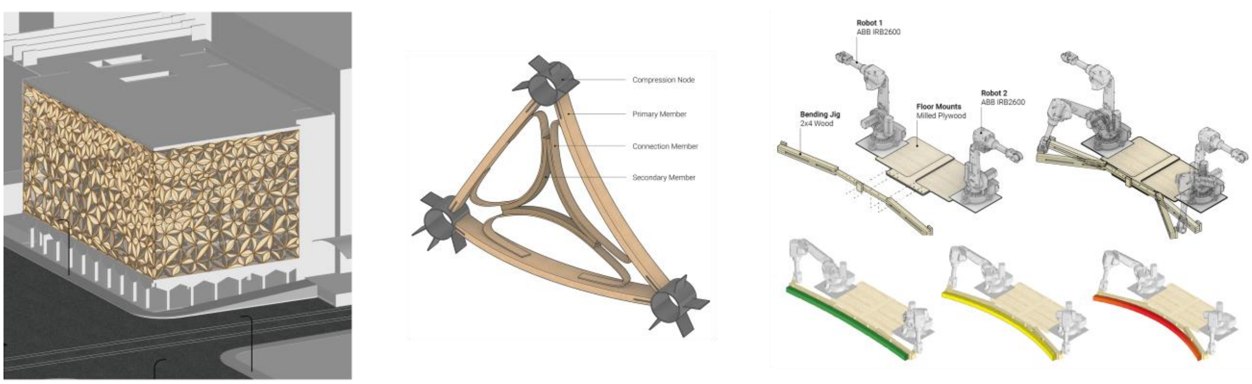
For each game scenario, one of the questionnaires listed above is used. The nature of the study, the audience involved, the tasks they are asked to complete, and the medium and length of each session are all factors to consider. Three stages of data collection and user interaction are suggested; First, a pre-study questionnaire is used to gather anonymous demographic data and provide unbiased details about the upcoming study. A mid-study questionnaire is a set of direct questions intended to evaluate the user's participation and study if the user can effectively use the tools provided for design. A post-study questionnaire will be used to verify the workflow. Also, it is used to demonstrate whether users have understood and engaged with the platform and to assess the environment's degree of immersion and credibility.

5 PILOT STUDY

A pilot study is chosen to put the aforementioned elements into practise. In this section, the elements of the established framework are described in detail, along with possible limitations and data collection procedures.

5.1 Pilot Study: Retrofitting a Building Façade Using Participatory Design Environments

The City Building and Design Lab (CBDL) in the heart of Calgary has been chosen for the pilot study. This 1962 building has concrete slabs and columns. The west and south facades of the building provide an opportunity for repurposing and retrofitting while leaving the carbon-intensive elements (slabs and columns) in place.



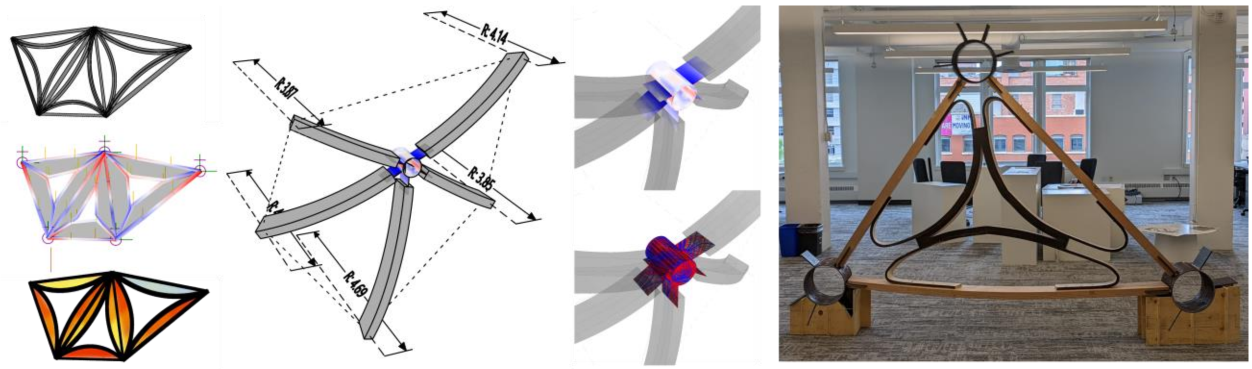
[1] [2]

Figure 3: Proposed high-performance facade based on automated timber construction for the CBDL building, Calgary. 1) Overall view for south and west facades. 2) Fabrication system.

The building will have a new facade based on automated timber construction techniques (Nahmad Vazquez and Walker 2021). Given the coworking nature of offices and educational spaces, CBDL is an excellent contender for the pilot project of the suggested workflow.

5.2 Framework Elements: Design Agencies and Performance Evaluation System

In the developed framework, tasks are designed in which the player can make design decisions and adjustments to the proposed design of the CBDL building. Three categories have been designed to provide information to the player: structural, environmental and manufacturing costs. The performance after each decision is shown to the player. The backend procedure (Figure 4) retrieves structural and environmental performance and examines geometrical properties for cost calculation.



[1] [2] [3] [4]

Figure 4: Various data embedded in the developed game environment. 1) structural and environmental performance. 2) geometrical constraint considering the manufacturing system. 3) additional analysis on details and joinery. 4) real-size prototype of the facade system.

A data set is created using an algorithm to assess the player's decision, generating possible random changes on the facade and performing different analyses on each transition. Performance between the old and new states is compared at every change. Five labels are allocated to each decision based on this comparison.

Further, five parameters are extracted in the structural performance category from the FEM analysis: a) Max displacement (Maximum deflection of all members), b) Total mass, c) Elastic internal energy change (scalar product of external nodal loads and nodal displacement), d) Von-Mises stress on principal plane stresses, $\sigma_v = \sqrt[2]{\frac{1}{2}\left[\left(\sigma_x - \sigma_y\right)^2 + \left(\sigma_y - \sigma_x\right)^2 + (\sigma_z - \sigma_x)^2\right] + 3\left(\tau^2{}_{xy} + \tau^2{}_{xy} + \tau^2{}_{xy}\right)}$, Where σ_α is normal stress in the α Direction and τ_θ is sheer stress in θ plane, and e) Beam utilization ratio (critical stress over allowable stress). Then, the overall performance of each choice is marked based on those five indicators, presuming that each one can be improved or made worse. By separating the domain of all possible performance grades into five subdomains, each design choice can be categorized as *very bad*, *bad*, *neutral*, *good*, and *very good*. That is, for every criterion C_i, the value for the transition from state A to state B is: $V_i(AB) = C_i(A) - C_i(B)$. Then the value is standardized as $V_i^* = \frac{V_i(AB) - mean(V_i)}{standard\ deviation\ (V_i)}$.

Lastly, the summation of all standardized values in every category, combined with weight factors, decides the label for this transition. For instance, Structural performance for a transition is calculated as $P_s(AB) = \sum_{k=1}^{5} W_k V_k^*$.

Labels are intended to be understandable by non-experts. For example, improvement in three or more criteria is considered a very good choice. It is important to emphasize that the framework keeps all the changes in the allowable range, meaning that an option leading to fatal failure cannot be generated. Two mechanisms were used during the data set creation step to accomplish this. First, when a new structure is constructed based on each state transition or choice, the minimal viable structure is created in this procedure by automatically changing the structural parameters. In this case, the option with the smallest available cross-section maintains the minimum or acceptable range for each of the five parameters. A similar process is applied for all other criteria. The second mechanism is that changes will be clamped to the nearest alternative that satisfies the performance criteria when a valid structure cannot be constructed (Figure 4).

.

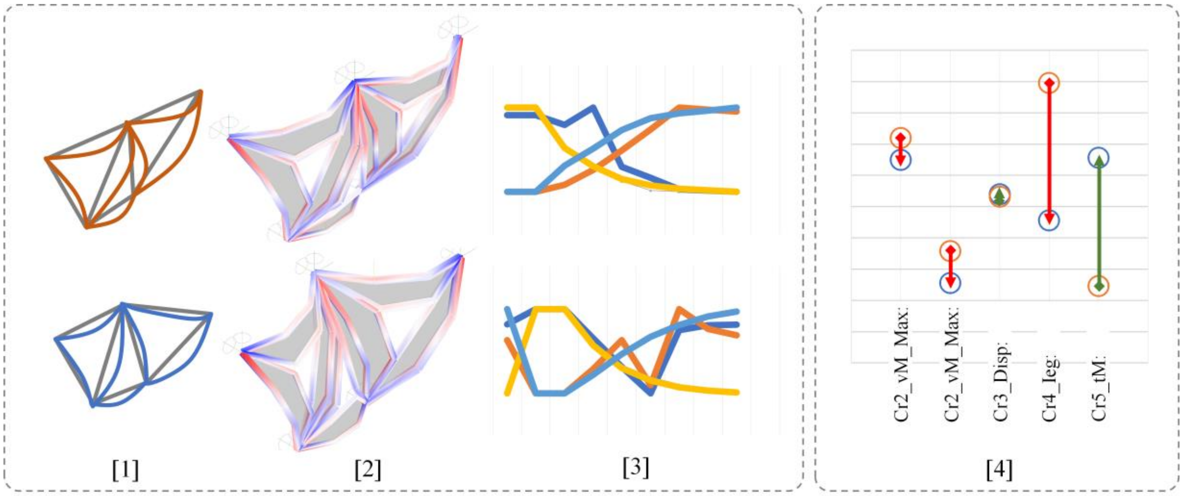


Figure 5: Structural data set generation for AI agent training procedure. 1) Two randomly generated states. 2) Finite element utilization preview. 3) Last iterations of optimization in five structural criteria. 4) Comparison of performance for evaluation of the transition.

The same principles are employed for three environmental criteria. These are a) total façade (direct) solar energy gain, b) interior sun exposure and c) free (unobstructed) sky view from inside. Desirable ranges are established depending on the location of the building and its context. A grade of five labels is assigned to each design choice. Similarly, for the fabrication feedback agent, the cost of material and fabrication and the constructability of members are two criteria for its training.

Another entity introduced to coexist alongside the player is the non-playing character (NPC). The simulated environment comprises the player, the NPCs and the three feedback systems. Players cannot be alone in an empty building; to create a more realistic and credible environment, agents or NPCs are designed to interact and behave like regular people who work in an office. The agents can only respond to the environment and communicate with one another; they cannot modify any game features. A public dataset from UCI Irvine is utilized for training this agent in the early stages of the proposed framework (Dua and Graff 2019). Accelerometer data from 15 participants engaged in seven everyday activities are included in the dataset compiled by Casale, Pujol, and Radeva (2012). This data set applies to training an agent with multi-target regression in an office setting. Data is labelled with similar types of behaviour as those found in an office environment (i.e. working at a computer, standing up and walking and going up\down stairs, standing, walking, going up\down stairs, walking and talking with someone, talking while standing). NPCs aim to be trained to be responsive to their surroundings. Hence, their behaviour and interaction with every option the player creates is another valuable information source.

5.3 Initial Study & Limitations

The initial study model is developed and ready for data collection (Figure 6). Pre-study questionnaires and briefings are the first steps in each session. In each participation session, the participant is asked to complete a series of selection tasks and modifications in the game engine. Changes are sent to the backend Python during the interaction. Trained models estimate performance and reply to the results encapsulated in the game engine and displayed through graphical user elements. Participants can end the session at any time, which prompts them to answer the final questionnaire. Each design task takes less than 10 minutes to complete in beta testing, and five tasks are designed. The third task includes a mid-game questionnaire (Figure 7).

Figure 6: Game environment based on pilot study for data collection (Developed using Unreal Engine).

Maintaining a real-time engagement with the user is one of the primary challenges in the cross-software framework. Higher pauses or response time, according to studies, may disturb decision-making. In other words, a successful design process requires an uninterrupted flow of information (Brady 1986; Jones and Reinhart 2018). Since this is related to the amount of information conveyed, data types and formats must be examined after each development step. Another issue involves the lack of previous similar studies to determine sample size (MacKenzie 2013). Also, as the framework aims to keep up with the multidisciplinary nature of design, the scope of discussion can be arguable. Therefore, the correlation and relation between any pair of sample groups need to be studied. The data gathering phase with the developed framework is anticipated in summer/fall 2023 in a professional (architectural office) and an educational setting (university students). The results will be published in a report, serving as the foundation for the framework's second iteration.

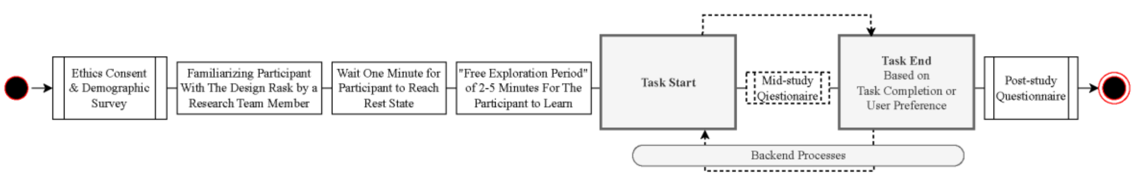


Figure 7: Participant workflow from the initial questionnaire, framework training and interaction to the final post-study questionnaire.

6 CONCLUSION

The proposed framework presents the first practical steps for embedding various data types into a holistic virtual design environment using game engines. A cross-disciplinary approach to design is discussed after examining the value and challenges of user assessment. The literature review discusses how and why all design forces can coexist in a game engine as new middle grounds or threshold spaces for design and communication with existing architectural design software are discussed. Two significant shortcomings of the developed design tools are deduced and shaped into two critical characteristics of novel data-driven design techniques employing game engines. The aim is to enhance users' perception and guide their decisions whilst providing user occupancy information at early design stages. Methods to validate the framework's usability and the characteristics derived from initial studies and partial reports are also mentioned. Finally, the suggested framework offers a novel method for designers to employ a collaborative, cross-disciplinary design system to get a qualitative understanding of end-users' complicated quantitative preferences through both direct and indirect assessment. The proposed design framework can result in socially responsible, economically viable, and environmentally sustainable designs which involve all stakeholders and allow for bottom-up negotiations and decision-making processes. Conflicts are minimized at this stage through mediation, limitation-aware rules, and data augmentation. Developing the design framework is the first stage of a three-year research collaboration. The next step will deploy the framework with different user groups to refine and iterate the process while gathering user preferences and behaviour data.

REFERENCES

Azar, E., W. O'Brien, S. Carlucci, T. Hong, A. Sonta, J. Kim, M. S. Andargie, T. Abuimara, M. El Asmar, R. K. Jain, M. M. Ouf, F. Tahmasebi, J. Zhou. 2020. "Simulation-Aided Occupant-Centric Building Design: A Critical Review of Tools, Methods, and Applications". *Energy and Buildings* 224, pp. 1-17.

Baños, R. M., C. Botella, M. Alcañiz, V. Liaño, B. Guerrero, and B. Rey. 2004. "Immersion and Emotion: Their Impact on the Sense of Presence." *CyberPsychology & Behavior* 7, pp. 734–741.

Baus, O., S. Bouchard, V. Gougeon, and F. Roucaut. 2011. "Comparison of Anxiety in Response to Virtual Spiders While Immersed in Augmented Reality, Head-Mounted Display, or CAVE-like System". *Journal of CyberTherapy and Rehabilitation* 4, pp. 171–175.

Brady, J. T. 1986. "A Theory of Productivity in the Creative Process". *IEEE Computer Graphics and Applications* 6, pp. 25–34.

Brooke, J. 1996. "SUS: A 'Quick and Dirty' Usability Scale". In *Usability Evaluation In Industry*, 1st Edition, 207–12. CRC Press.

Brooke, J. 2013. "SUS: A Retrospective". *Journal of Usability Studies* 8 , pp. 29–40.

Casale, P., O. Pujol, and P. Radeva. 2012. "Personalization and User Verification in Wearable Systems Using Biometric Walking Patterns". *Personal and Ubiquitous Computing* 16, pp. 563–580.

Chen, Y., X. Luo, and T. Hong. 2016. "An Agent-Based Occupancy Simulator for Building Performance Simulation". *ASHRAE Annual Conference*.

Christiansson, P., K. Svidt, K. B. Pedersen, and U. Dybro. 2011. "User Participation In The Building Process". *Journal of Information Technology in Construction* 16, pp. 309–335.

Dong, B., and B. Andrews. 2009. "Sensor-Based Occupancy Behavioral Pattern Recognition For Energy And Comfort Management In Intelligent Buildings". *Building Simulation 2009 - 11th International IBPSA Conference*, pp. 1444-1472

Dong, B., and K. P. Lam. 2011. "Building Energy and Comfort Management through Occupant Behaviour Pattern Detection Based on a Large-Scale Environmental Sensor Network". *Published Online* 4, pp. 359–369.

Dua, D., and C. Graff. 2019. "{UCI} Machine Learning Repository, University of California, Irvine, School of Information and Computer Sciences, 2019". http://archive.ics.uci.edu/ml. Accessed March 2, 2023.

Dufresne, D. 2022. "NFB: Fort McMoney". National Film Board of Canada. 2022. https://www.nfb.ca/interactive/fort_mcmoney/. Accessed March 11, 2023.

Edwards, G., H. Li, and B. Wang. 2015. "BIM Based Collaborative and Interactive Design Process Using Computer Game Engine for General End-Users". *Visualization in Engineering* 3, pp. 1–17.

Eiris, R., and M. Gheisari. 2017. "Research Trends of Virtual Human Applications in Architecture, Engineering and Construction". *Journal of Information Technology in Construction (ITcon)* 22, pp. 168–184.

Erickson, V. L., M. Á. Carreira-Perpiñán, and A. E. Cerpa. 2011. "OBSERVE: Occupancy-Based System for Efficient Reduction of HVAC Energy". *Proceedings of the 10th ACM/IEEE International Conference on Information Processing in Sensor Networks*.

Finstad, K. 2010. "The Usability Metric for User Experience". *Interacting with Computers* 22, pp. 323–327.

Grier, R. A., A. Bangor, P. Kortum, and S. C. Peres. 2013. "The System Usability Scale". *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, pp. 187–191.

IronPython Contributors, Microsoft Corporation, and Python Software Foundation. 2013. "IronPython". https://ironpython.net/documentation/. Accessed March 6, 2023.

Iversen, O. S., K. Halskov, and T. W. Leong. 2010. "Rekindling Values in Participatory Design". *PDC '10: Proceedings of the 11th Biennial Participatory Design Conference*, pp. 91–100.

Jia, M., R. S. Srinivasan, and A. A. Raheem. 2017. "From Occupancy to Occupant Behavior: An Analytical Survey of Data Acquisition Technologies, Modeling Methodologies and Simulation Coupling Mechanisms for Building Energy Efficiency". *Renewable and Sustainable Energy Reviews* 68.

Jones, N. L., and C. F. Reinhart. 2018. "Effects of Real-Time Simulation Feedback on Design for Visual Comfort". *Journal of Building Performance Simulation* 12, pp. 343–361.

Kanthila, C., A. Boodi, K. Beddiar, Y. Amirat, and M. Benbouzid. 2021. "Building Occupancy Behavior and Prediction Methods: A Critical Review and Challenging Locks". *IEEE Access* 9, pp. 79353–79372.

Khosrowpour, A., R. Gulbinas, and J. E. Taylor. 2016. "Occupant Workstation Level Energy-Use Prediction in Commercial Buildings: Developing and Assessing a New Method to Enable Targeted Energy Efficiency Programs". *Energy and Buildings* 127, pp. 1133–1145.

Kleban, S. D., W. A. Stubblefield, K. W. Mitchiner, J. L. Mitchiner, and M. Arms. 2001. "Collaborative Evaluation of Early Design Decisions and Product Manufacturability". *Proceedings of the Hawaii International Conference on System Sciences*, 270.

Kwak, D., A. Kam, D. Becerra, Q. Zhou, A. Hops, E. Zarour, A. Kam, L. Sarmenta, M. Blanchette, and J. Waldispühl. 2013. "Open-Phylo: A Customizable Crowd-Computing Platform for Multiple Sequence Alignment". *Genome Biology* 14, pp. 1–12.

Lee, C., J. C. K. Tong, and V. Cheng. 2014. "Occupant Behavior in Building Design and Operation". *HK Joint Symposium 2014*.

Lewis, J. R. 2009. "IBM Computer Usability Satisfaction Questionnaires: Psychometric Evaluation and Instructions for Use". *International Journal of Human–Computer Interaction* 7, pp. 57–78.

Lewis, J. R. 2018. "Measuring Perceived Usability: The CSUQ, SUS, and UMUX". *International Journal of Human–Computer Interaction* 34, pp. 1148–1156.

Li, X., and R. Yao. 2020. "A Machine-Learning-Based Approach to Predict Residential Annual Space Heating and Cooling Loads Considering Occupant Behaviour". *Energy* 212.

Lin, C., and P. Hsu. 2017. "Integrating Procedural Modelling Process and Immersive VR Environment for Architectural Design Education". *MATEC Web of Conferences - IC4M & ICDES* 104.

MacKenzie, I. Scott. 2013. "Human-Computer Interaction :An Empirical Research Perspective". San Francisco: Elsevier Science & Technology. ProQuest Ebook Central.

Madrazo, L., Á. Sicilia, and A. M. Cojo. 2009. "BARCODE HOUSING SYSTEM Integrating Floor Plan Layout Generation Processes within an Open and Collaborative System to Design and Build Customized Housing". *CAADFutures*.

Nahmad Vazquez, A., and M. Walker. 2021. "Balancing Design and Performance: Multi-Objective Optimization for Generation of High-Performance Façade Panels for Retrofitting". *SimAUD 2021, Symposium on Simulation for Architecture + Urban Design*.

Nelson, H. G., and E. Stolterman. 2014. *The Design Way: Intentional Change in an Unpredictable World.* MIT press.

Parvin, A. 2013. "Architecture (and the Other 99%): Open-Source Architecture and Design Commons". *Architectural Design* 83, pp. 90–95.

Peng, Y., A. Rysanek, Z. Nagy, and A. Schlüter. 2018. "Using Machine Learning Techniques for Occupancy-Prediction-Based Cooling Control in Office Buildings". *Applied Energy* 211, pp. 1343–1358.

Python Software Foundation. 2010. "Python, Amsterdam: Centrum voor Wiskunde en Informatica". https://www.python.org/. Accessed March 16, 2023.

Robert McNeel & Associates. 2020. "Rhinoceros 3D, Seattle: Robert McNeel & Associates". https://www.rhino3d.com/7/new/. Accessed March 16, 2023.

Saeidi, S., Ch. Chokwitthaya, Y. Zhu, and M. Sun. 2018. "Spatial-Temporal Event-Driven Modeling for Occupant Behavior Studies Using Immersive Virtual Environments". *Automation in Construction* 94, pp. 371–382.

Schubert, T., F. Friedmann, and H. Regenbrecht. n.d. "Igroup Presence Questionnaire (IPQ)". http://www.igroup.org/pq/ipq/. Accessed March 16, 2023.

Schultz, C., M. Bhatt, and A. Borrmann. 2017. "Bridging Qualitative Spatial Constraints and Feature-Based Parametric Modelling: Expressing Visibility and Movement Constraints". *Advanced Engineering Informatics* 31, pp. 2–17.

Schwind, V., P. Knierim, N. Haas, and N. Henze. 2019. "Using Presence Questionnaires in Virtual Reality." *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, pp. 1-12

Shiratuddin, M. F., and W. Thabet. 2011. "Utilizing a 3D Game Engine to Develop a Virtual Design Review System." *Journal of Information Technology in Construction* 16, pp. 39–68.

Sonta, A. J., P. E. Simmons, and R. K. Jain. 2018. "Understanding Building Occupant Activities at Scale: An Integrated Knowledge-Based and Data-Driven Approach". *Advanced Engineering Informatics* 37, pp. 1–13.

Sun, H., H. V. Burton, and H. Huang. 2021. "Machine Learning Applications for Building Structural Design and Performance Assessment: State-of-the-Art Review". *Journal of Building Engineering* 33, pp. 1-13.

Sun, Y., F. Haghighat, and B. C. M. Fung. 2020. "A Review of The-State-of-the-Art in Data-Driven Approaches for Building Energy Prediction". *Energy and Buildings* 221, pp. 1-20.

Wang, C., D. Yan, and Y. Jiang. 2011. "A Novel Approach for Building Occupancy Simulation". *Building Simulation 2011 4:2* 4, pp. 149–167.

Wazoku. n.d. "InnoCentive: Solve the World's Greatest Challenges". https://www.innocentive.com/. Accessed November 4, 2022.

Wei, Y., X. Zhang, Y. Shi, L. Xia, S. Pan, J. Wu, M. Han, and X. Zhao. 2018. "A Review of Data-Driven Approaches for Prediction and Classification of Building Energy Consumption". *Renewable and Sustainable Energy Reviews* 82, pp. 1027–1047.

Woodbury, R. F., S. J. Shannon, and A. D. Radford. 2001. "Games in Early Design Education". *Computer Aided Architectural Design Futures 2001*, pp. 201–214.

Yan, D., T. Hong, B. Dong, A. Mahdavi, S. D'Oca, I. Gaetani, and X. Feng. 2017. "IEA EBC Annex 66: Definition and Simulation of Occupant Behavior in Buildings". *Energy and Buildings* 156, pp. 258–270.

AUTHOR BIOGRAPHIES

ALICIA NAHMAD VAZQUEZ is an architect and entrepreneur. She works as assistant professor at the SAPL, University of Calgary. She holds a PhD in human-robot collaborative (HRC) design from Cardiff

University. She is the founder of Architecture Extrapolated (R-Ex) and The Circular Factory. Before joining SAPL she worked as studio master at the Architectural Associational Design Research Laboratory (DRL) 'master's program. Alicia explores materials and digital design and fabrication technologies along with the digitization of building trades and the wisdom of traditional building cultures. Her email is alicia.nahmadvazquez@ucalgary.ca.

ARMAN KHALILBEIGI KHAMENEH is a digital architect. He is a Ph.D. student in environmental design at the University of Calgary with a focus on novel performance-aware design platforms. He focuses on design computation and incorporation of cutting-edge or customized manufacturing technologies into the design process in both his profession and teachings. His email is arman.khalilbeigikha@ucalgary.ca.