Assessment of an Agent's Wayfinding of the Urban Environment Through Reinforcement Learning

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This simulation study explores wayfinding motivated behavioral patterns in the city through agent-based modelling. Agents were trained using Unity's ML-Agents toolkit with reinforcement learning. The study uses the Sultan Ahmet Mosque and its surrounding boundary as a model environment for the training of an agent's wayfinding. Agents are trained to locate the Sultan Ahmet Mosque target. The behaviors of agents trained with two different methods, "Complex" and "Simple" learning, comparing their navigation quests at various difficulty levels featuring respawn points. After the training of the agents, the alternative routes produced while attaining the target during the wayfinding process were analyzed. As an outcome of the analysis, it was observed that the agents were prone to go off-route, navigate to different locations they perceived in the urban space, and then would reach the target. This occurrence is justified as an agent's curiosity trained through reinforcement learning. This study differs from the literature in a way that it attempts to understand the navigational behavior of agents that were trained with reinforcement learning. Moreover, this research discusses the perception of wayfinding through curiosity and aims to make a comprehension of the perception of the city, which is one of the key ideas in neurourbanism. The study contributes to the literature by showing that wayfinding behaviors acquired from agents' curiosity-driven explorations and past experiences can be an input for neurourbanism, supporting urban design. It informs urban enhancements that are user-centric and rich in urban perception using the reinforcement learning method.

Received: 08.07.2024
Accepted: 25.08.2024

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Imhemed, M. M. E., & Uzun, C. (2024). Assessment of an agent's wayfinding of the urban environment through reinforcement learning. *JCoDe: Journal of Computational Design and Engineering*, 5(1), 259-278.
https://doi.org/10.53710/jcode.1512798

Keywords: Behavioral Patterns, Motivational Curiosity, Neurourbanism, Reinforcement Learning, Urban Design.

Pekiştirmeli Öğrenme Yoluyla Bir Etmenin Kentsel Çevrede Yol Bulma Değerlendirilmesi

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Bu çalışma kentte yön bulma odağındaki davranış kalıplarını etmen tabanlı model üzerinden analiz eder. Çalışmanın hedefinde pekiştirmeli öğrenme ile yön bulmayı öğrenen etmenlerin davranışlarını anlamak bulunmaktadır. Çalışmanın hedefi doğrultusunda kullanılan yöntem etmen tabanlı modelleme olmuştur. Etmenler pekiştirmeli öğrenme ile Unity ML-Agents kullanılarak eğitilmiştir. Çalışma Sultan Ahmet Camii ve çevresini etmenin eğitimi için örnek bir çevre olarak almaktadır. Etmenler Sultan Ahmet Camii'yi bulmak hedefinde eğitilmiştir. Karmaşık ve basit öğrenme olarak iki farklı yöntemle eğitilen ve farklı başlangıç noktalarında yön bulma görevlerine başlatılan etmenlerin davranışları karşılaştırılmıştır. Bu çalışma pekiştirmeli öğrenme ile eğitilen etmenlerin yön bulma davranışlarını anlamaya çalışması bakımından literatürden farklılaşmaktadır. Bir diğer yönden bu araştırma yön bulma algısını merak kavramı üzerinden tartışmakta ve nöro-şehircilikte önemli kavramlardan olan kent algısını etmenler üzerinden anlamaya çalışmaktadır. Etmenlerin eğitilmesi sonrasında etmenlerin yön bulma sürecinde hedefe ulaşırken ürettikleri alternatif güzergahlar analiz edilmiştir. Analiz sonucunda, etmenlerin güzergah dışına çıkarak, kentsel mekanda algıladığı farklı konumlarda gezebildiği ve sonrasında hedefe ulaştığı görülmüştür. Bu durum pekiştirmeli öğrenme ile eğitilen etmenin merakı olarak açıklanmıştır. Etmenlerin merak odaklı keşiflerinden ve geçmiş deneyimlerden elde edilen yön bulma davranışları, kentsel tasarımı destekleyecek n nöro-şehirciliğin bir girdisi olabilmesi yönünde çalışma literatüre katkıda bulunmaktadır. Bu çalışma, kentte yön bulma davranış kalıplarının; kullanıcı odaklı ve kentsel algı açısından zengin kentsel alanların geliştirilebilmesinde pekiştirmeli öğrenme yöntemi ile katkıda bulunmaktadır.

Anahtar Kelimeler: Davranışsal Kalıplar, Motivasyon Merakı, Nöro-Şehircilik, Pekiştirmeli Öğrenme, Kentsel Tasarım.

Teslim Tarihi: 08.07.2024
Kabul Tarihi: 25.08.2024

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Imhemed, M. M. E., & Uzun, C. (2024). Pekiştirmeli öğrenme yoluyla bir etmenin kentsel çevrede yol bulma değerlendirilmesi. *JCoDe: Journal of Computational Design and Engineering,* 5(1), 259-278. https://doi.org/10.53710/jcode.1512798

1. INTRODUCTION

Neurourbanism studies the interlink between neuroscience, psychology, and urban planning to concordantly understand how a city's environment influences individuals' urban perception, cognitive function, and their navigation of it (Adli et al., 2017). As a result of escalating urban growth and the challenges that come with it, this research field came to be (Pykett et al., 2020). Adding to the cognitive perception and thus function of a city, neurourbanism looks to appropriate urban environments through considering elements like urban design and essentially how it can shape a user's perception and navigation (Salesses et al., 2013). This study subject matters because it is imperative for designing cities in the way that strengthens the link concerning a city's perception along with its navigational plans (Jeffery, 2019).

In the field of neurourbanism, the integrations of machine learning (ML) algorithms, like reinforcement learning (RL), are paving the way for meaningful interactive environments through their additions of cognitive and perceptive functions that come with developing urban spaces (Makanadar, 2024; Son et al., 2023). RL involves systems inhibited by self-referential agents that consequently learn from their actions (Sutton & Barto, 1999). With this framework, it has the potential of managing urban pathway routes as well as suggesting better navigational systems as a way of shaping efficient urban systems that assist city perception in users (Williamson, 2019; Ghazal et al., 2021). RL may assist urban planners in generating adaptive environments that respond to changing conditions and community needs by facilitating data-driven decisions and using agent-based modeling techniques (Cutitoi, 2022). This integration is vital in endorsing the improvement of cities that are both efficient in navigation as well as conducive to psychological and cognitive perceptions.

To examine the multi-layered relationship that connects RL and neurourbanism, studying different user behavioral trends in an area accentuates the prospective to design environments that value navigational urban perception (Portugali & Haken, 2018). Through learning from environmental data, RL can be used to heighten urban planning methods that come alongside bettering navigational routes in a city, allocating wayfinding solutions, and even through analyzing behavioral patterns that individuals may showcase in a space (Zhang et al., 2022). Additionally, conclusions from these methods in neurourbanism can contribute to the use of RL agents in urban environments by studying their capability to mimic certain human decision-making qualities and perceptual responses (As et al., 2022).

Neurourbanism's main idea revolves around neural processes that affect and guide a users' urban perception of a city. With this idea in mind, it relates to the understanding of the behavior of the flâneur, who is an urban explorer that curiously perceives and navigates the city in a detailed manner (La Rocca, 2017; Murail, 2017; Leomi, 2015). In this context, the flâneur then connects to the task of a RL agent in the concept of neurourbanism where just like the urban explorer, the agent curiously navigates their digital environment with the goal of perceiving it as a whole and making sense of it (Botteghi et al., 2021; Nilsson, 2011). So, through mirroring this exploratory behavior of the flâneur, agents can be deployed in mimicked environments where they can uncover behavioral patterns and trends that can inform urban planning to be more user-centric with a principal theme of perceptive wayfinding. Holding a promise of augmenting urban spaces that better align with urban perception, this unique synergy between RL and the foundations of neurourbanism supports the idea designing environments that increase perceptual and navigational quality (Heino, 2020; Phillips et al., 2015).

2. A FUSION OF NEUROURBANISM AND REINFORCEMENT LEARNING

The fusional synthesis of the field of neurourbanism and the algorithm of RL offers a conventional method to urban design in a way that uses this algorithm to enhance the cognitive perceptiveness of an urban space (Bibri et al., 2024). Considering neurourbanism's attentiveness on cognitive functional effects in urban environments, using RL gives designers the chance to dynamically correlate these concepts as its agents learn from interactions within an urban system with the intent of bettering it (Arbib, 2021). As a way of addressing differing urban implications posed by urbanization, this fusion allows urban designers to create urban spaces that advocate for proactively adding urban perception quality (Banczyk & Potts, 2018).

Neurourbanism stresses the creation of urban environments that offer cognitive functionality to residents in the way that is sets out a perceptive framework that re-imagines urban planning (Ndaguba et al., 2022). The study by Ndaguba et al. (2022) identifies central themes in neurourbanism research, including cognitive perception and urban stress, where it accents the prominence of urban spaces in reducing psychological strain, increasing cognitive clarity, as well as creating perceptually and thoughtfully designed environments. By forming a link between urban studies and neuroscience, neurourbanism can enlighten the expansion of urban layouts and systems that boost users' quality of life, thus specifying a framework for future urban planning and design initiatives (Baumann et al., 2020).

Neurourbanism also highlights the link between perceptual engagement and navigation with urban planning and design, in the way that it improves cognitive function (Xu et al., 2023; Küçük & Yüceer, 2022). Urban perception and wayfinding, that includes street perception and enclosure, impressions an individual's city perception and their navigational techniques through urban planning, correlates with neurourbanism's aim of spaces that generate functional cognitive clarity (Tolunay, 2022). Görgül and Özkan's study (2024) concluded that the outlined street silhouettes surrounded by elements affected the sense of spatial clarity of users and their perception of that specific space.

In the subject of urban design, RL algorithms are employed to analyze pedestrian pathway suggestions and controlling the flow of traffic in roads (Ye et al., 2021). These algorithms are able to make adaptive modifications that add to the perceptual quality of an urban environment, in the process that they continuously learn from the system's real-time information (Zhang et al., 2022). RL can also, in the quest to make urban environments more conductive to cognitive function, be employed in advocating for enhanced sensory stimuli in an urban layout (As et al., 2022; Tewari et al., 2023; Kee & Ho, 2024). Expending RL to develop urban navigational strategies also involves the redesign of space usage and spatial street layouts by suggesting better-suited pathways (Zheng et al., 2023; Son et al., 2023; Han et al., 2021).

RL, curiously motivated in the urban context, uses intrinsic behaviors to develop exploratory perceptions in an environment layout (Botteghi et al., 2021; Huang et al., 2021). With the foundations of urban explorations that are shaped by motivational curiosity, this approach can be applied to RL agents that actively navigate and explore environmental layouts. In the way that they learn from their actions and their consequences like humans do, these agents essentially mimic a human being's intrinsic curiosity (Deshpande et al., 2021). This method can be used in prioritizing the explorations of unfamiliar urban spaces to suggest efficient navigational map coverages (Botteghi et al., 2021).

Linking RL methods with urban design has the prospective to suggest contemporary navigational outputs that are motivated by users' curiosity-driven behavioral patterns (Bouton et al., 2019; Makanadar, 2024). Bearing in mind neurourbanism's concentration on urban perception effects in environments (Küçük & Yüceer, 2022), its intersection with curiosity-motivated RL can cultivate navigation and wayfinding in cities (Ye et al., 2021). This interaction between the two fields aims to design urban spaces that are perceptive in their cognitive functionality, reflecting neurourbanism's ideology that is advocating for a city's urban perception (Görgül & Özkan, 2024; Zheng et al., 2023).

The constant change in user preferences as well as the shifting social and environmental conditions calls for conventional design methodologies. With these concepts, simulation studies let designers mimic complex real-world scenarios using RL algorithms (Intrator & Intrator, 2001), that feature training agents to learn from their actions in an alike way to how a human being would. Simulation studies can help in providing design solutions through the investigations of an agent's curiosity-motivated behavioral patterns in an urban context. Moreover, using Unity's ML-Agents toolkit (Juliani et al., 2018) allows urban scenarios to be simulated in a digital environment where agents learn through curiosity-motivated explorations, as a contemporary approach to study multi-layered urban systems that traditional methods struggle to analyze. Featuring agents with the attitude of the flâneur and using an agent-based model (ABM) simulation (Macal & North, 2009), this study analyzes the behavioral patterns suggested by an agent's curiosity-motivated exploration. It focuses on the Sultan Ahmet Mosque neighborhood in Istanbul, examining how curiosity, an intrinsic motivation (Silvia, 2012), influences an agent's behavior in navigating and understanding their surroundings through the behavioral patterns and trends it showcases in real-time.

3. METHODOLOGY

This study employs an ABM simulation in union with RL to explore the impact of curiosity on an agent's behavioral patterns within Istanbul's Sultan Ahmet Mosque neighborhood (**Figure 1**). ABM simulates individual agent behaviors in complex systems used to theorize very complex virtual environments that are resided by independent and self-referential agents (Macal & North, 2009). For this study, this ABM simulation method is applied in use of an RL algorithm, where the agent strategizes to make decisions and learns efficient navigational patterns through interactions based on the feedback, through its model brain, it obtains from the system being either positive or negative. "Rewards" are positive reinforcements awarded to the agent and processed within their brains because of desirable behavior that motivate them to continue this behavior, whereas "Punishments" are negative reinforcements that are a result of undesirable behavior that discourage them from repeating certain behaviors (Sutton, 1992). Unity's ML-Agents toolkit facilitates this process, providing an open-source platform for the creation of simulated environments where RL teaches agents through rewards and punishments (Juliani et al., 2018). The Unity ML-Agents toolkit comprises sensors, agents, and an academy that manage simulation steps and agent interactions, where agents mimic human behaviors to enhance learning efficiency (Lanham, 2018).

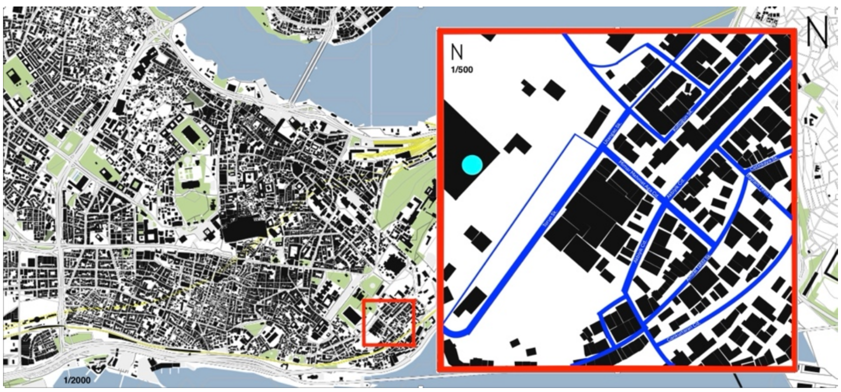


Figure 1: The Sultan Ahmet site with landmark. (map from schwarzplan.eu).

3.1 Study Area and Its Design Criteria

The reason that this neighborhood was selected is because the Sultan Ahmet Mosque is widely known by many as an iconic landmark and its reputations as a tourist attraction, built in 1916, and serving as a symbol and integral part of Istanbul's cultural, historical, and religious identity. The Sultan Ahmet Mosque neighborhood environment, modelled in 3D and scaled for performance (**Figure 2**), enables testing within a simplified urban setting. In terms of its physical features and attributes, it was modelled as simple as possible, excluding urban elements like trees, most physical features such as roads, and moving objects like people for testing purposes. In this study, the environment's building blocks, and side walls have box colliders with the "Is Trigger" option enabled to trigger punishments when the agent interacts with them, signaling undesirable actions (Engelbrecht, 2023). The agent's target, a sphere representing the Sultan Ahmet Mosque, also has a box collider to trigger rewards, guiding the agent's behavior towards the landmark.

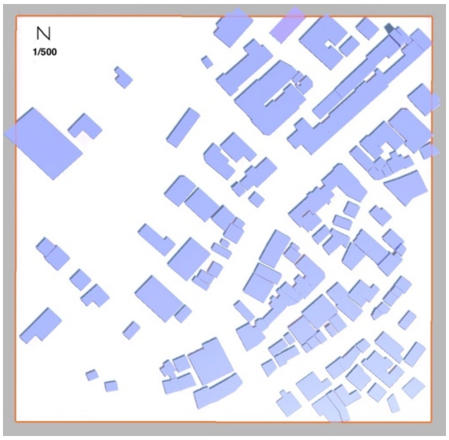


Figure 2: Sultan Ahmet neighbourhood digital environment (created by author).

The agent is designed as a minimal cube for simplicity. It represents the flâneur as an urban explorer, navigating the urban environment for the first time. The agent interacts with the environment and other objects through a box collider and a Rigidbody component, allowing it to physically navigate the space. To simulate human-like perception, a Ray Perception Sensor 3D component is attached to the agent. This sensor enables the agent to detect objects and respond accordingly by acquiring rewards and punishments, depending on the type of object detected. For example, the agent earns rewards when it detects an object tagged as "PinBall" and receives a punishment when encountering an object tagged as "Wall" (**Figure 3**). This setup is intended to mimic human peripheral visions and perception, helping the agent navigate the environment more efficiently.

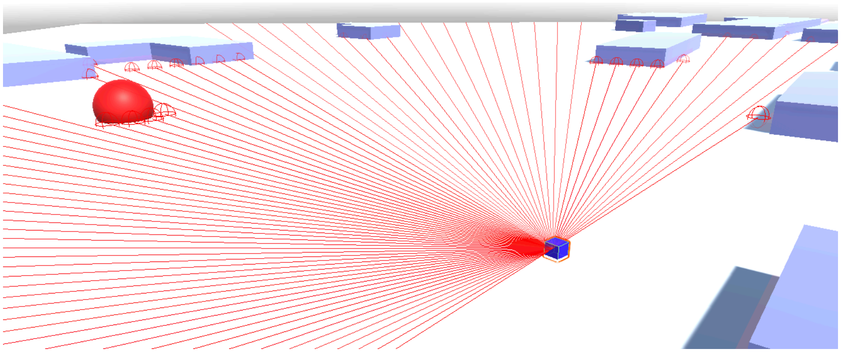


Figure 3: Agent's perception sensors detecting environment (created by author).

3.2 Model Training and Evaluation

The reward design in Unity's Python C# script guides the agent's brain to make decisions and improve over time during the training process (Juliani et al., 2018). The agents' training process includes the start of their actions at the beginning of each episode, which also features indicating where the respawn locations occur, as well as their actions throughout the environment. The agents' actions are shaped by the consequences they receive, so rewards are desirable outcomes and punishments are negative ones. During training, agents' performances are monitored, and behavioral patterns are analyzed, guiding agents toward preferred outcomes and enhancing their decision-making abilities (Engelbrecht, 2023).

Training involved 6,000,000 steps conducted over a total of 300 minutes, simulating the agents' behavior as if they were on a continuous 5-hour exploration in the study area. This simulation compared two types of agents: one with a "Simple" brain model and another with a "Complex" brain model, using Unity's Inference behavior training (Juliani et al., 2018). The "Complex" agent constantly updates its decision-making processes in real-time, mimicking a more adaptive and responsive cognitive function. This model was designed to emulate a curiosity-driven approach, where the agent is motivated to explore novel stimuli and adjust its behavior based on newly acquired information. In contrast, the "Simple" brain model lacks this update feature and operates with a fixed decision-making process, which limits its ability to explore and adapt.

The study aimed to compare the effect of curiosity on behavioral patterns of both the agents in their quest to find the target (Sultan Ahmet Mosque). The curiosity component is integral to the "Complex" agent’s ability to seek out new paths and adapt to spontaneous events, thereby enhancing its navigational abilities. To ensure robustness, the simulation comparison was run a couple of times to reduce potential biases and provide a clear understanding of how curiosity affects behavioral patterns.

The training process was done across varying difficulty levels, as “Easy”, “Medium”, and “Difficult” (**Figure 4**). The different levels were opted according to the kinds of routes that were able to be taken by the agent, their perceptibility, and their distance from the target. This is where each agent’s respawn location begins during the training. For instance, the “Easy” path has a higher perceptibility and is closer to the target (approx. 500m), whereas the “Difficult” path has a lower perceptibility and is further from the target (approx. 510m). This was done to further compare their curiosity impacted behaviors in different respawn points, testing whether a further location to the target or a cluster of buildings in the agents’ way affects the behavioral trends in search of the target.

Figure 4: Agent’s difficulty level starting locations (created by author).

This study's evaluation method involved detailed observation of the agent's exploratory paths to the target. Each training session was meticulously recorded, tracking routes on a diagram of the digital environment. These routes were categorized and color-coded to reflect their frequency of use: "Primary", shown in orange, represent the most frequently taken paths: "Secondary" routes, shown in blue, indicate the second most frequently taken paths; and "Random" routes, shown in pink, correspond to infrequent and non-repetitive paths that the agent took at random intervals.

4. FINDINGS AND DISCUSSION

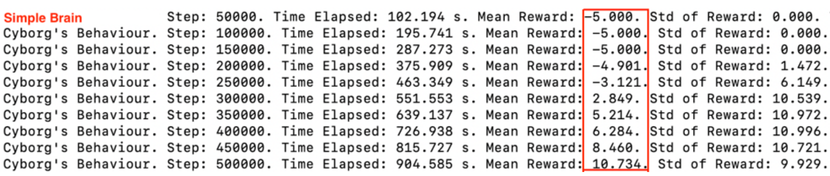
In the “Easy” level, both “Complex” brain and “Simple” brain agents predominantly followed the same primary path, with the “Simple” brain agent exhibiting greater random path exploration because of its lack of memory in effective routes (**Figure 5**). In the “Medium” level, the “Simple” brain agent continued exploring varied paths driven by curiosity, while the “Complex” brain agent increasingly relied on learned, shorter paths that led it to the target (**Figure 6**). In the “Difficult” level, both agents showcased very similar path preferences and trends, however the “Complex” brain agent contrastingly displayed slightly more diverse random paths (**Figure 7**).

Figure 5: Agent’s “Easy” level behavior pattern (created by author).

Figure 6: Agent’s “Medium” level behavior pattern (created by author).

Figure 7: Agent's "Difficult" level behavior pattern (created by author).

Among all three difficulty levels, the agents' behaviors displayed the influences of curiosity and the impertinence of learned experiences in the navigation process. The "Simple" brain agent's widespread exploration of random paths in the deficiency of an updated data brain underlines the intrinsic motivation of curiosity in pathfinding (**Figure 8**). Contrarywise, the "Complex" brain agent's dependence on its updated data to recall effectual routes exemplifies the guidance of experience on decreasing exploratory behaviors over time, as it earned more rewards overtime (**Figure 9**). This study's discoveries illuminate the convoluted interaction concerning curiosity, experience, and navigational performance in independent agents in an urban setting.



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Simple Brain          Step: 50000. Time Elapsed: 102.194 s. Mean Reward: -5.000. Std of Reward: 0.000.
Cyborg's Behaviour. Step: 100000. Time Elapsed: 195.741 s. Mean Reward: -5.000. Std of Reward: 0.000.
Cyborg's Behaviour. Step: 150000. Time Elapsed: 287.273 s. Mean Reward: -5.000. Std of Reward: 0.000.
Cyborg's Behaviour. Step: 200000. Time Elapsed: 375.909 s. Mean Reward: -4.901. Std of Reward: 1.472.
Cyborg's Behaviour. Step: 250000. Time Elapsed: 463.349 s. Mean Reward: -3.121. Std of Reward: 6.149.
Cyborg's Behaviour. Step: 300000. Time Elapsed: 551.553 s. Mean Reward: 2.849. Std of Reward: 10.539.
Cyborg's Behaviour. Step: 350000. Time Elapsed: 639.137 s. Mean Reward: 5.214. Std of Reward: 10.972.
Cyborg's Behaviour. Step: 400000. Time Elapsed: 726.938 s. Mean Reward: 6.284. Std of Reward: 10.996.
Cyborg's Behaviour. Step: 450000. Time Elapsed: 815.727 s. Mean Reward: 8.460. Std of Reward: 10.721.
Cyborg's Behaviour. Step: 500000. Time Elapsed: 904.585 s. Mean Reward: 10.734. Std of Reward: 9.929.
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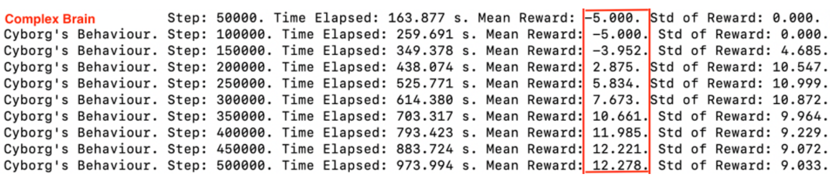
Figure 8: Agent's "Simple" brain's learning rate (created by author).



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Complex Brain         Step: 50000. Time Elapsed: 163.877 s. Mean Reward: -5.000. Std of Reward: 0.000.
Cyborg's Behaviour. Step: 100000. Time Elapsed: 259.691 s. Mean Reward: -5.000. Std of Reward: 0.000.
Cyborg's Behaviour. Step: 150000. Time Elapsed: 349.378 s. Mean Reward: -3.952. Std of Reward: 4.685.
Cyborg's Behaviour. Step: 200000. Time Elapsed: 438.074 s. Mean Reward: 2.875. Std of Reward: 10.547.
Cyborg's Behaviour. Step: 250000. Time Elapsed: 525.771 s. Mean Reward: 5.834. Std of Reward: 10.999.
Cyborg's Behaviour. Step: 300000. Time Elapsed: 614.380 s. Mean Reward: 7.673. Std of Reward: 10.872.
Cyborg's Behaviour. Step: 350000. Time Elapsed: 703.317 s. Mean Reward: 10.661. Std of Reward: 9.964.
Cyborg's Behaviour. Step: 400000. Time Elapsed: 793.423 s. Mean Reward: 11.985. Std of Reward: 9.229.
Cyborg's Behaviour. Step: 450000. Time Elapsed: 883.724 s. Mean Reward: 12.221. Std of Reward: 9.072.
Cyborg's Behaviour. Step: 500000. Time Elapsed: 973.994 s. Mean Reward: 12.278. Std of Reward: 9.033.
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Figure 9: Agent's "Complex" brain's learning rate (created by author).

Distinctive behavioral patterns surfaced with a link to the agent and how it behaves when motivated by curiosity during the observational interpretations of the training sessions, exhibiting sufficient conceptions into their navigation movements and their pathway tendencies. Interestingly, the agents kept taking the paths they continuously recognized. In addition, with the "Simple” brain agent, it found a moderately easy or straightforward path that directed it towards the target, and it continued to take that path and overlooked perplexing routes. From the agent’s curious perception of the city, it became familiar with certain routes through repetitive exposure to the environment, this familiarity developing from its repeated encounters with the environment which allowed it to cultivate a basic understanding of the layout. With a "Simple” brain model present, the agent’s familiarity is not the actual result of true learning in the sense of adapting behaviors, based on rewards or feedback, and instead it unintentionally “learned” certain paths simply by repeated interaction with them.

When the results are considered in the light of neurourbanism, it is interpreted that these behavioral trends, which showcase the agent’s route preferences, strengthens the idea of environmental familiarity in the way that it leads navigational behaviors. These study’s comprehensions align with neurourbanism with the emphasis on cognitively perceptive urban design suggestions. Evaluating these results through the perspective of neurourbanism suggests that while environmental familiarity can adhere for navigation efficiency, true cognitive adaptation and resilience require mechanisms that enable agents, and by extension humans, to dynamically respond to changing urban context through meaningful interactions. This method therefore presents a promising avenue for exploring and bettering urban designs that promote urban cognitive perception, strengthening the link between RL and neurourbanism.

The discussion identifies several limitations of this study that impact its applicability in real-world architectural contexts, despite providing valuable insights into curiosity-influenced behavior. Firstly, the simulation used a small and simplified sample size of an Istanbul neighborhood, which may not fully capture the complexity of its urban features such as trees, monuments, and other physical features. Additionally, the study did not incorporate moving objects, such as people or vehicles, which are crucial components of real urban environments. When importing the site map into Unity, it was scaled down to simpler dimension due to the original size’s complexity and computational rendering constraints. These modifications may limit the generalizability of the results. Furthermore, while the simulation provides a controlled environment for studying agent behavior, it may not entirely mimic the realness aspect and the unpredictability of urban environments, human behavior, and perception.

5. CONCLUSION

To study the influence that curiosity has on agents' behavioral trends in Istanbul's Sultan Ahmet Mosque neighborhood, this study used an RL algorithm approach in an ABM simulation. The methodology integrates ABM to simulate individual agent behaviors in complex systems, using Unity's ML-Agents plug-in, and RL algorithms to expediate decision-making and learning through consequences. This approach enabled the agents to engage in curiosity-driven navigation, which significantly influenced their exploration and movement patterns.

The findings reveal that curiosity-driven navigation led agents to exhibit distinctive behavioral patterns, particularly in their exploration of different areas within the urban environment. This behavior was evident as agents developed unique path preferences, repeatedly using the Sultan Ahmet Mosque as a reference point to construct a comprehensive mental map of the environment. The study stresses that repetitive exposure and experience, driven by curiosity, influentially shape these navigational behaviors.

Specifically, the exploration of curiosity in agents revealed distinctive differences in behavior across three types of difficulty levels associated with their respawn locations in the environment. The study found that:

a) Curiosity does certainly influence the agent as it motivated it to explore different areas of the environment, developing unique path preferences and using the Sultan Ahmet Mosque target as its point of reference to create a comprehensive mental map of the environment.

b) During the RL learning process, architects can form interactions with the agent through making modifications and controlling the C# script reward design, where they can give instructions, ultimately communicating with it.

c) From such experiences, architects, urban designers and planners can use this approach to generate adaptive design solutions by testing it in different simulated urban scenarios that imitate real-life agendas, to explore behavioral patterns and user preferences.

In conclusion, the findings offer insights to urban planners and designers, emphasizing the potential of curiosity-driven navigation in shaping behavioral patterns and cognitive responses in urban spaces. This approach can be used in elevating and generating adaptive design solutions by testing it in different simulated urban scenarios that imitate real-life settings, to explore behavioral patterns and preferences. Integrating the principles of neurourbanism, this study features the potential of incorporating neuroscientific insights and RL agents to design urban environments that are psychologically perceptive. Ultimately, by understanding how different urban forms affect human behavior and cognitive responses, urban planners and designers can adhere for urban spaces that encourage cognitive perceptiveness and function. Neurourbanism advocates for considering the human brain's response to the built environment, and so this approach allows for the simulation and refinement of urban designs based on real-world psychological and behavioral data.

Acknowledgements

This research study is based on the master's thesis titled "A Cyborg's Perception of the City" supervised by Assist. Prof. Dr. Can Uzun.

Conflict of Interest Statement

The manuscript is entitled "Assessment of an Agent's Wayfinding of the Urban Environment Through Reinforcement Learning" has not been published elsewhere and that it has not been submitted simultaneously for publication elsewhere.

Author Contribution

The authors declare that they have contributed equally to the manuscript.

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