Unraveling Collaborative Formation: A Framework of Investigating Key Factors Shaping Landscape Architecture Professions in the Era of Digital Visualization

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Abstract: The integration of data science, machine learning, and artificial intelligence in landscape architecture, urban studies and design promises transformative impacts on cities. While acknowledging that urban complexities transcend data, the concepts of datafication and dataism emphasize the potential to sample, model, and predict urban phenomena through data. This study explores the synergy of digital visualization in collaboration. A structured framework, rooted in the multidimensional collaboration model and guided by theories, elucidates dimensions like Governance, Administration, Autonomy, Mutuality, Norms, and Equality. An illustration of qualitative research prepared for a second phase quantitative research complements the framework, aiming to discover indicators to assess the impact of data visualization on collaboration formation. This study contributes to structuring the framework to examine the symbiotic relationship between data visualization, collaboration, and decision-making, propelling transformative landscape architecture and urban data governance.

Keywords: Digital visualization, framework, collaboration, decision-making, communication, interaction

1 Introduction

The utilization of data science, machine learning (ML), and the broader field of artificial intelligence (AI) in urban studies and design is poised to make a significant impact on cities in the coming years. While it is important to acknowledge that urban complexities cannot be entirely reduced to data, a concept known as datafication (CUKIER & MAYER-SCHÖNBERGER 2014), there is a growing recognition, referred to by journalists and cultural observers as dataism (HARARI 2016), that many aspects of urban life can be effectively sampled, modeled, and predicted through the data that represents them. Data science and machine learning, as intersecting disciplines, encompass various topics with their respective sets of pros and cons (Fig. 1). The application of ML and AI to landscape architecture and cities is particularly notable because it involves employing computers to sift through vast amounts of data, distill the essential elements of each phenomenon, and focus on the significant aspects. This process enables algorithms to operate with a certain level of autonomy, making decisions and drawing conclusions that must ultimately be evaluated by humans, who are responsible for attributing meaning to these symbolic representations. Given the inherently interdisciplinary nature of landscape architecture, urban design and planning, along with related fields like civil engineering and municipal engineering (MOUDON 1992, VAN ASSCHE et al. 2012), the establishment of comprehensive guidelines has become imperative at various levels of government and within organizational structures. Whether functioning as part of a team or as individual representatives, experts supported by guidelines contribute to meticulous decision-making and the generation of innovative design solutions.

Journal of Digital Landscape Architecture, 9-2024, pp. 420-431. © Wichmann Verlag, VDE VERLAG GMBH · Berlin · Offenbach. ISBN 978-3-87907-752-6, ISSN 2367-4253, e-ISSN 2511-624X, doi:10.14627/537752038.

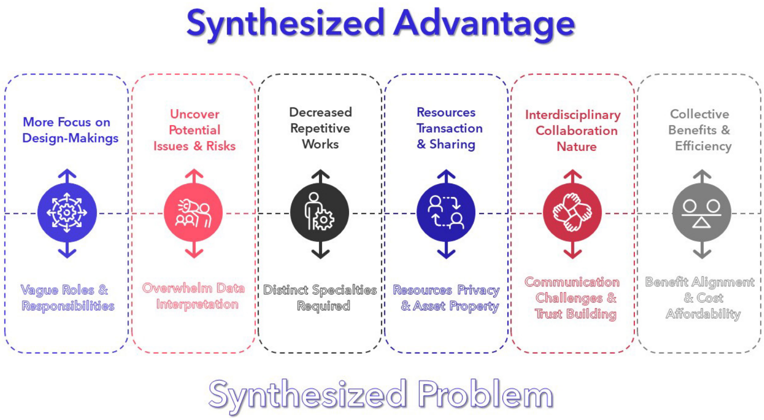

Fig. 1: Synthesized advantage and problem of utilizing digital visualization during the collaboration in landscape architecture, urban design and planning

2 Case Studies

A compelling illustration of this collaborative approach is exemplified by Tang et al.'s work (TANG et al. 2020). They developed an interactive interface serves not only as a communication conduit among decision-makers but also as a guiding framework that steers designers through predefined spatial criteria. Another example is CityMatrix, a creation of MIT Media Lab, specifically designed to streamline user interaction by eliminating the need for prior expertise and ensuring a user-friendly learning curve (ZHANG 2017). This innovative system enables users to seamlessly incorporate, remove, or interchange modules, fostering a dynamic environment for designing, interacting, and enhancing collaboration among participants and machines. The integration of data applications has also gained substantial traction in city projects, as demonstrated by the Miami-Dade Interactive Tool (MIAMI-DADE TRANSPORTATION PLAN 2022). This tool, accessible to the public, enables comprehensive engagement in processing and shaping new projects, while also serving as an internal resource for governmental departments involved in funding allocation, performance assessment, and project prioritization.

It is important to emphasize that while interactive interfaces facilitate stakeholder engagement, they do not supplant the roles of decision-makers and designers. Instead, these roles are intricately defined based on specific tasks assigned during different phases of collaboration. While the terms "decision-makers" and "designers" encapsulate distinct responsibilities, their allocation can be a product of contextual considerations, collaboratively determined to suit the unique circumstances at hand. Their fundamental and optimal function revolves around catalysing the process through meaningful interactions. This entails striking a harmonious equilibrium between adhering to rigorous protocols and fostering the emergence of novel design solutions.

The practice of design and planning demands a keen awareness among professionals regarding the inherent correlation and interchangeability between decision-making and design solutions within the workflow. Flexibility in both domains stands as a foundational consideration. Moreover, a comprehensive grasp of the core tasks involved and their reciprocal influences assumes paramount importance. Presently, ongoing research endeavours are dedicated to investigating, developing, and showcasing the integration of data science analysis, visualization, and prediction within the realm of data governance.

Paskaleva et al. (PASKALEVA et al. 2017) draw upon case studies from Europe and stakeholder surveys to illustrate the pivotal role of data governance in underpinning smart cities and sustainable development solutions. Cuno et al. (CUNO et al. 2019) introduce the innovative concept of an Urban Data Space (UDS), aiming to form an essential component of tools necessary for the sustainable transformation of German and European cities. In the context of Toronto, SCASSA (2020) and ARTYUSHINA (2020) employ distinct approaches to explore issues and extract key lessons related to data governance through their respective lenses. These pioneering initiatives strive to provide empirical evidence and illustrative instances that shed light on the effective application of digital visualization. This application is particularly pertinent to decision-making processes, guided by forward-looking perspectives that align with technological advancements and the trajectory of data governance.

3 Framework Development

3.1 Structuring the Framework

The realm of research has thus far offered limited focus on the fundamental comprehension of effectively harnessing data visualization in collaborative pursuits to achieve shared interests within the domain of digital landscape architecture, urban design and planning. The concept of collaboration holds considerable importance, not only spotlighting the dynamic interplay between humans and data, but also highlighting the intricate interactions among individuals through various mediums. Additionally, this concept unveils a systematic trajectory for potential progress in urban data governance, while also shedding light on the strategic deployment of visualization techniques. This is particularly pertinent within projects that revolve around the concept of smart cities, where the fusion of these elements could drive transformative advancements.

In order to establish a robust and empirically validated theory of collaboration that enhances both theoretical understanding and practical application within the realms of digital landscape architecture, urban design, and planning, this article presents a framework for developing, measuring, and validating collaborative indicators. This framework places particular emphasis on the utilization and influence of data visualization in digital applications, inquiries, and communication. It comprises two phases: qualitative and quantitative. Phase 1 – qualitative research aims to gather firsthand data through observations and interviewed narratives, understanding current working performance or collaboration. Phase 2 – quantitative research employs a questionnaire for using multivariate methods to simultaneously analyse the weighted impact of collaborative dimensions facilitated by digital techniques and data visualization.

Expanding upon Phase 1, the collaborative dimension is further refined and extended, drawing upon the multidimensional collaboration model introduced by THOMSON et al. (2007), which encompasses elements of governance, administration, organizational autonomy, mutuality, and norms. Furthermore, an additional dimension, “Equality”, is introduced to assess the equilibrium between individual and collective interests. Importantly, to build upon the top-down theorized dimension, Phase 1 qualitative research approach is employed to collect substantial data through observations and interviews in collaborative practices (KVALE 2008). These inquiries and narratives unveil intricate details and practical insights. During the bottom-up transcription process, keywords are extracted to serve as catalysts for honing and reshaping the dimensions that encapsulate the collaborative efforts involved in the application of digital techniques and data visualization in the fields of landscape architecture, urban design, and planning.

Within the context of the reshaped dimension, my goal is to initiate Phase 2 survey aimed at preparing for a statistical validation process as the quantitative method. The purpose of this survey and the quantitative research is to gain a deeper understanding of weighted indicators, which have been transformed by the incorporation of keywords and are associated with the refined collaborative dimension. The construction of the questionnaire will be based on Phase 1 and Thomson et al.'s framework (THOMSON et al. 2007), with the subsequent application of a Structural Equation Model (SEM) that encompasses both a measurement and a structural aspect. The primary objective is to conduct a rigorous evaluation of the statistical significance and validity of the research model through iterative refinement. Through a combination of hierarchical qualitative research and quantitative analysis, I intend to explore how collaboration is shaped by the use of digital techniques and data visualization. This holistic approach will provide valuable insights into the dynamics of collaboration in the context of digital landscape architecture, urban design, and planning.

3.2 Collaborative Dimensions Development

Through an extensive review of existing literature, I have meticulously re-identified and crafted the six distinct dimensions demonstrated to serve as the focal points of my study (Fig. 2). These dimensions provide a comprehensive framework that not only guides the trajectory of my research but also ensures a rigorous validation process. The first dimension, “Governance”, scrutinizes the intricate interplay between data visualization, designers, and decision-makers, shedding light on their interdependent roles. The second dimension, “Administration”, delves into the tangible elements that underpin decision-making processes, lending concrete substance to their implementation. The third dimension, “Autonomy”, lays bare the pivotal and far-reaching consequences of decision-making, elucidating their profound impact on collective and organizational interests. The fourth dimension, “Mutuality”, intricately examines the various facets of collaboration in data-driven urban design, unraveling the components that foster successful partnerships. The fifth dimension, “Norm”, ventures into the realm of trust by exploring the essential factors that underlie effective decision-making processes. Lastly, the sixth dimension, “Equality”, embarks on a quest to uncover the subtle yet crucial congruence between collective aspirations and organizational interests. This dimension is specifically incorporated to explore potential congruency and identify possible differences. For instance, the application of AI in an enterprise is studied to discern primary needs among departments. The top-funded departments are expected to have interests aligned with the company's collective goals, while departments receiving less sponsorship may face limitations in pursuing their interests in the short term. In this scenario, an analysis of the percentage achievement of departments' interests becomes crucial for developing a resource distribution strategy in the near future. This investment initiates a new exploration to define rules that influence other dimensions, such as governance, thereby starting a loop for a continuous collaborative examination as an ongoing improvement. Each dimension is underpinned by pertinent theories meticulously selected to bolster its development, culminating in a set of incisive research questions. These carefully crafted inquiries will serve as the bedrock for devising meaningful indicators, enabling a more profound exploration in subsequent stages of this research endeavour.

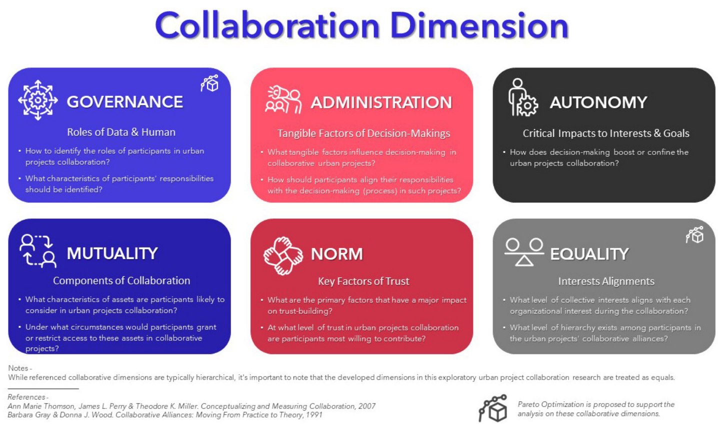

Fig. 2: Developed collaboration dimension for investigating key factors of utilizing digital visualization during the collaboration in landscape architecture, urban design and planning

Amidst my review of existing literature, I focus on the theories advanced by Gray and Wood (GRAY & WOOD 1991). These theories, alongside social-economic and public policy frameworks, provide a robust lens for understanding high-level collaboration. I have compared these theories with collaboration studies, leading me to center my research on digital visualization's influence on collaborative formation. In the governance dimension, Corporate Social Performance Theory (CARROLL 1979, WARTICK & COCHRAN 1985, WOOD 1991, WOOD 1991, PRESTON & POST 2013) and Institutional Economics Theory (LIVINGSTON 1987, SÖDERBAUM 1987, WHALEN 1987, QUIGGIN 1988, BROMLEY 1989) illuminate the delineation of collective goals and participants' roles. Administration, influenced by Strategic Management Theory (GARTNER & PORTER 1985, HOFER & SCHENDEL 1996) and Social Ecology Theory (ASTLEY & FOMBRUN 1983, ASTLEY 1984, FOMBURN 1986), guides strategies for equitable task allocation. The autonomy dimension draws from Microeconomics Theory (COASE 1937, WILLIAMSON 1975, BAUMOL & WILLIAMSON 1986, WILLIAMSON 1991) to address challenges in collaboration dynamics. Mutuality, inspired by Resource Dependence Theory (NIENHÜSER 2008, HILLMAN et al. 2009, DAVIS & COBB 2010, BIEMANN & HARSCH 2016), urges scholars to explore the alignment of individual and collective interests. Turning to the norm dimension, Institutional Theory and Negotiated Order Theory (DIMAGGIO & POWELL 1983) underscore the significance of norms and tacit understanding in nurturing lasting collaborations. Lastly, the equality dimension, anchored in Political Theory (DAHL 1969, BENSON 1975, SANZONE & WILDAVSKY 1979, KEOHANE, 1984, STRANGE 1989), probes the synergy of organizational and collective interests. This research incorporates Gray and Wood's theories (GRAY & WOOD 1991), emphasizing an exploration of the diverse impacts of digital visualization on decision-making, design solutions, and data governance which are the behaviors and instruments that have played a crucial role in shaping collaboration.

3.3 Framework Utilization

The framework combines both quantitative and qualitative research methods to formulate multidimensional indicators for evaluating the influence of digital visualization on collaborative practices in urban and landscape architecture. The primary goal of this framework is to reveal the intricate connections between digital visualization and critical collaborative factors.

The collaborative workflow in urban and landscape architecture practice operates in a hybrid digital format. In the course of Phase 1 – qualitative research, targeted activities play a crucial role in directing the discussion and distilling essential insights related to digital visualization and data applications. Data integration is a central element employed to streamline tasks and missions within this workflow. Prominent missions and events encompass tasks involved with but are not limited to Midjourney, ChatGPT, ML, AI, extended reality (XR) and Building Information Modelling (BIM).

During Phase 1 field research, it is essential to employ a method or instrument that serves as a guide for distinguishing between field tasks and research tasks. Field tasks involve activities such as concept brainstorming, design development, digital model generation, parametric logic development, and decision-making discussions. On the other hand, research tasks aim to delve deeper into insights and narratives, documenting facts derived from field tasks to illustrate interactive behaviors. These research tasks serve as the medium for associating with multidimensional indicators.

The instrument employed is a proposed timeline that maps the formation of collaboration based on the top-down theorized dimensions (Fig. 3). By comparing the progression of collaborative formation with the typical design workflow, researchers can effectively manage field tasks and collect and transcribe data for research development. The goal is not to rigidly adhere to the top-down theorized dimensions and their weighted indicators but to uncover the dynamics of collaborative formation within the context of digital visualization integration.

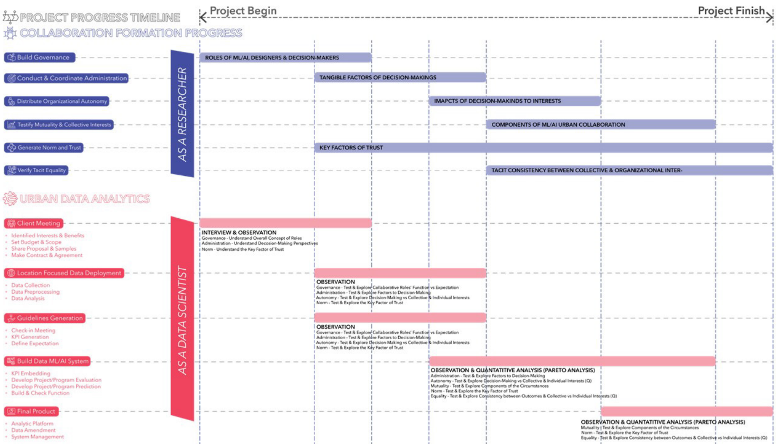

Fig. 3: An example of timeline comparison between studied collaboration formation and a project workflow

The application of the Phase 1 qualitative framework involves meticulous observation and interview procedures. Formatted interviews have been organized to engage participants with experience and interests in the practical application of digital visualization and AI. To mitigate bias in perspectives, participants are classified into two primary groups: designers, including architects, landscape architects, and urban designers; and decision-makers, such as urban analysts and planners, along with other stakeholders. Additionally, secondary actors, such as developers, technical specialists, and tool developers, are also included.

The categorization of participants is based on their significant roles within the collaborative workflow. This approach aims to facilitate the development of a holistic spectrum, illustrating the concurrent understanding and phenomenon of using digital visualization in collaboration. The notes from these interviews are then entrusted to the conductor for transcription. Each activity transcribed during this phase serves as a valuable resource for extracting keywords. For instance, an activity is described wherein 'an urban designer informally defines Midjourney for assisting in rendering (Fig. 4).' In this context, we can extract the finite and transitive verb 'define' and use it to correlate this activity with the relevant collaborative dimension. Moreover, the objective is to identify the tool and/or method utilized in this activity, discerning the specific aspect of data visualization intended for application. The guidelines for extraction are delineated below, outlining the pertinent information to distill for research analysis concerning collaboration within the human-machine relationship.

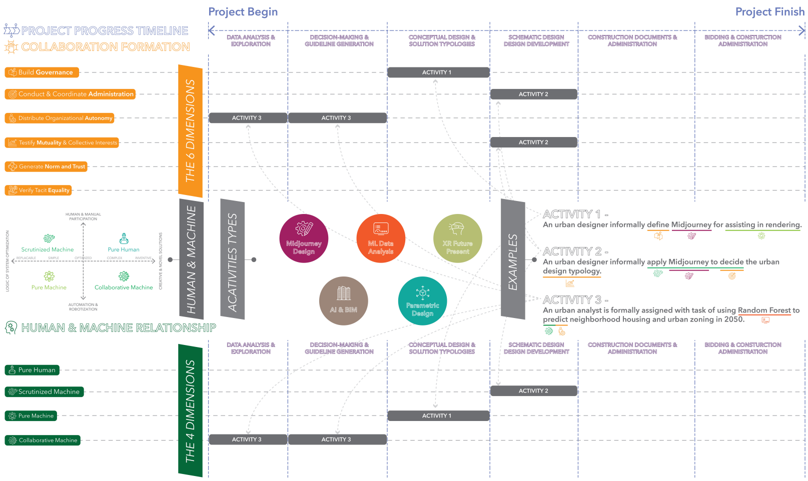

Fig. 4: Phase 1 – Qualitative Research Framework: Keyword extraction and corresponding collaborative dimensions

Guidelines for Selecting Keywords for Information Matching:

1. Collaboration Dimension:
   a. Governance: Words or phrases describing actions of setting mindset, rules, guidelines, or regulations. Example: “The manager 'identifies' AI as crucial for the urban planning project integration.”
   b. Administration: Words or phrases for describing aggregated actions or behaviors. Example: “The group of urban designers 'coordinates' the urban design format with Midjourney's assistance.”

   c. Autonomy: Words or phrases describing the level of independent work. Example: “An urban planner 'relies on' machine learning for decision-making.”
   d. Mutuality: Words or phrases describing reciprocal assets or approaches. Example: “The director negotiates by offering 'the capability of designing and customizing urban analytic system platforms' to the government client.”
   e. Norm: Words or phrases describing trust, faith, and belief. Example: “A government agent 'feels confident' signing a long-term contract using Building Information Modeling (BIM).”
   f. Equality: Words or phrases describing the balance between investments and rewards. Example: “The project manager 'recognizes the team’s higher work performance' with AI assistance.”

2. Techniques and/or Data Visualization:

   Words or phrases describing tools or methods used in projects. Examples include but are not limited to Midjourney, machine learning (ML), artificial intelligence (AI), parametric methods, CAD, BIM, etc.

3. Human and Machine Relationship:
   a. Scrutinized Machine: Words or phrases describing tasks completed or processed with machine assistance under human supervision or oversight. Example: “An urban designer 'applies Midjourney' to decide urban design typology.”
   b. Pure Human-Machine: Words or phrases describing tasks completed or processed only by humans. Example: “Urban project managers and directors 'coordinate AI investments' in collaborative projects.”
   c. Pure Machine: Words or phrases describing tasks completed or processed solely by machines. Example: “Urban design 'rendering is processed with Midjourney's assistance'.”
   d. Collaborative Machine: Words or phrases describing tasks completed or processed by human-machine interaction. Example: “The interdisciplinary team 'uses machine learning-generated output to discuss' subsequent impacts and strategies.”

By assigning each activity to a specific stage on the workflow timeline, we can tally the frequency of each dimension along with the tools and/or methods utilized. This analysis provides insights into the nature of the relationship between humans and machines based on how these tools and methods are applied in practice.

Utilizing the established workflow derived from qualitative research, the envisioned collaboration between humans and machines seeks to reveal prevalent phenomena. Following this phase, Phase 2 questionnaire will be developed, inviting both initial interviewees and additional participants using the same rationale to provide anonymous feedback. The aim of this subsequent questionnaire is to quantitatively measure statistical values that illuminate the weighted impact of each collaborative dimension influencing the ongoing collaboration. This exploration specifically focuses on the integration of digital techniques and methodologies in data visualization.

To obtain the weighted impact validated by statistical and quantitative methods, the questionnaire will be designed based on the outcomes from phase 1. This will further delve into the indicators associated with collaborative dimensions. For instance, a sample question could be: “Departments understand the primary needs of using digital visualization in urban projects”. The format will follow a Likert scale ranging from 1 (not at all) to 7 (totally agree).

Collected data from the questionnaire will then undergo analysis and calculations through SEM. This approach will help explore the weighted impacts of collaborative indicators and provide a validated model for future examinations related to collaboration applying digital visualization.

4 Discussion

The research framework is currently advancing through Phase 1, focused on developing a qualitative research methodology. This will extend into Phase 2, where the emphasis will shift towards quantitative research. An anticipated outcome from Phase 1 is a studied spectrum presented in a statistical format, such as a heat map table. This format will effectively illustrate impactful indicators, serving as guidelines for designing the questionnaire in Phase 2. The overarching goal of this framework is to provide valuable insights for enterprises or institutions assessing collaborative performance in utilizing digital technologies and data visualization.

However, this structured research method has its limitations. Firstly, for successful implementation, it requires primary personnel to possess a comprehensive understanding of the collaborative workflow, applied techniques, and the concept of collaboration. Given the intricate nature of collaboration in landscape architecture, and urban design and planning, researchers may find it challenging to strictly adhere to predefined guidelines. This may introduce biases in the outcomes as the existing knowledge base may still contain subjective concepts. It is recommended that the conductor engages in discussions to gain a deeper understanding of the underlying reasons.

Secondarily, a potential source of bias lies in the diversity and quantity of collected data. To enhance this method, adopting a systematic approach to data collection could benefit the conductor by mitigating data bias. Lastly, echoing the point mentioned in the previous paragraph, the outcomes may quickly become outdated due to advancements in technology. Therefore, an ambitious expectation is the exploration of an automated system for verifying established knowledge and ensuring data remains updated.

5 Conclusion

By delving into the allocation of resources and the advantages achieved through established norms and innovative data interpretation techniques, I introduce a structured framework designed to assess the extent to which data visualization is integrated into urban projects. Simultaneously, my objective is to shed light on the intricate relationship between digital visualization and its impact on human-machine interaction and the collaboration. By applying this framework, I aim to provide a fundamental understanding of the central role played by digital visualization and to elucidate its interconnectedness with the formation of collaboration in the fields of landscape architecture, urban design and planning.

While acknowledging the inherent challenges stemming from the complexity of urban professionals and the relatively early stage of data science application in urban projects, it is important to recognize that uncovering all positive impacts may be a challenging task. However, despite these challenges, I am excited to share a research method that can contribute to the advancement and exploration of collaborative approaches through data visualization.

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