AI-driven decision support for SCRUM team selection in smart city software development projects

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Abstract
Objectives: This study proposes a machine learning-enabled application designed to support project management in selecting optimal SCRUM development teams for smart city software projects. These projects exhibit significant variability in complexity, ranging from localized initiatives to large-scale government-level applications. The solution aims to enhance decision-making by aligning team configurations with project goals, complexity, and resource constraints. **Prior work**: Building on established SCRUM and SAFe frameworks, the research leverages prior studies analyzing role distribution within development teams across four scenarios. These scenarios range from minimal setups with a single Business Analyst (BA) to complex configurations involving a Product Owner (PO) and a Product Manager (PM). The work addresses the challenges of adapting team roles to diverse project demands, particularly in the context of smart cities. **Approach**: The research employs a case-study methodology, combining quantitative data from more than 50 professionals across more than 25 companies and qualitative interviews with three experts. A machine learning model incorporates these empirical insights to recommend team structures tailored to project-specific characteristics and historical success metrics. **Results**: The application accurately identifies the most suitable SCRUM team configurations for diverse project criteria. Validation results indicate improved outcomes, such as reduced development time, enhanced team productivity, and better alignment with stakeholder expectations. **Implications**: This research provides academics and practitioners with tools to systematically optimize SCRUM team structures. It addresses the unique complexities of smart city projects, offering scalable solutions for various levels of project intricacy. **Value**: By integrating AI-driven insights with practical SCRUM principles, this study delivers a novel approach to managing smart city software projects. It bridges the gap between theoretical frameworks and the dynamic demands of real-world applications, ensuring scalability and efficiency.

Keywords: smart cities governance, urban innovation, agile project management, team configuration, role distribution

1. Introduction

The rapid modernization of urban environments and the global push for enhanced infrastructure have positioned smart cities at the forefront of technological innovation.

These cities leverage advanced technologies to improve resource management, elevate public services, and enhance the overall quality of life for citizens. But the rise of smart city projects brings new problems in managing software projects because they are more complicated and have different needs from stakeholders. These needs range from small localized apps to large government-wide deployments.

Agile methodologies, particularly SCRUM, have become integral in managing the complexities of software development projects. In the context of smart cities, optimizing SCRUM team configurations is crucial due to the diverse stakeholders and evolving project requirements inherent in these initiatives. While existing research, such as [1], which examines excellence practices in SCRUM, has explored general team configuration strategies, the unique demands of smart city projects necessitate a more tailored approach.

Integrating machine learning into team formation processes offers a dynamic solution to these challenges. In [2], AI-driven smart cities in France are presented, mostly about using AI technologies to help cities grow. Our research, on the other hand, suggests using machine learning to create an app that changes the structure of SCRUM teams based on the needs of each project. This method resolves the issues with traditional static team structures discussed in previous research. It makes the framework for developing software for smart cities more flexible and quicker to respond to changes.

New research on the effects of skill-driven models on SCRUM teams in software projects [3] has also pointed out the need for flexible skill sets. This study fits in with those findings. But smart city projects are more complicated because they involve many stakeholders, changing needs, and adding new technologies. This implies a more organized approach to team structure optimization. This differentiates our work from that of Ade et al. [4], which focuses on the broader integration of Big Data and AI for real-time decision-making in smart cities without specifically addressing SCRUM team optimization.

Using real-life examples from case studies and interviews with experts, our suggested solution creates a model that correctly figures out the best team structures based on the needs of the project and measures of past success. This study fills in the gaps between theoretical frameworks and the changing needs of real-world applications. This makes sure that managing smart city software projects is both scalable and effective.

While SCRUM traditionally emphasizes the central role of the Product Owner (PO), smart city projects often require broader skill sets within the development team, extending into the domains of Business Analyst (BA) and Product Manager (PM). These additional competencies are particularly critical during the early stages of planning, where tasks such as stakeholder analysis, requirement gathering, and goal prioritization are foundational. Although SCRUM frameworks leave the implementation of these skills flexible within the team, the absence of clearly defined roles can lead to inefficiencies and misalignment in complex projects.

This paper explores three distinct SCRUM team configurations: (1) a PO acting as both PO and BA, (2) a PO supported by a team member with BA skills, and (3) a PO supported by two team members with BA and PM skills. By analyzing real-world scenarios and employing a machine learning model, we aim to provide a systematic tool to optimize team structures tailored to the demands of diverse smart city projects.

The research methodology employed in this study is a case-study approach, combining quantitative data from more than 50 professionals across more than 25 companies and qualitative interviews with three experts in the field of smart city software development. The quantitative data collection involved gathering information on successful SCRUM team configurations, project complexities, and outcome metrics across a range of software projects. The qualitative interviews were conducted with product owners and business analysts to gain deeper insights into the challenges and best practices of adapting SCRUM team structures to the unique demands of different projects.

We organized the rest of the paper as follows. The next section provides an overview of SCRUM methodologies in software development, emphasizing their application within smart city projects. Section 3 reviews related work on team configuration and optimization in agile frameworks. Section 4 outlines our proposed machine learning-enabled application, detailing its development and implementation. Section 5 presents the results derived from case studies and expert interviews. Finally, Section 6 concludes the paper by summarizing our contributions and suggesting avenues for future research.

2. Specificities of smart city projects

Smart city projects stand out due to their inherent complexity, unique requirements, and the direct impact they have on urban populations. Unlike traditional software initiatives, these projects integrate multiple domains such as urban planning, environmental management, and public administration. The interplay between cutting-edge technologies and real-world infrastructure creates a distinctive environment that necessitates tailored approaches to project management. Moreover, their scope varies significantly, encompassing localized solutions like smart parking systems and expansive endeavors such as national e-government platforms. This diversity underscores the importance of adaptable and scalable methodologies in addressing their challenges.

2.1. Why are smart city projects different?

Smart city projects differ from conventional software development initiatives primarily due to their multifaceted nature and the dynamic interplay of diverse factors. Smart city projects often require seamless collaboration between public authorities, private entities, and citizens. The integration of cutting-edge technologies like IoT, AI, and cloud computing, often functioning alongside legacy systems, further amplifies this complexity [5]. Additionally, the outcomes of these projects have a profound and direct impact on citizens' daily lives, necessitating a high level of usability, reliability, and stakeholder involvement.

The scalability of these projects makes them unique: urban mobility app may apply one city, while national traffic management system address diverse regional requirements. This variability in scope demands flexible methodologies that can accommodate projects of differing sizes and complexities. Furthermore, smart city projects often involve long-term strategies, necessitating robust frameworks for iteration and evolution over time.

Lastly, the requirements of smart city projects are not only technical but also socio-political. Achieving alignment among stakeholders with differing priorities—ranging from public sector efficiency to private sector profitability and citizen satisfaction—is critical. Such alignment calls for a nuanced understanding of stakeholder dynamics and the ability to mediate conflicting objectives effectively. These things make smart city projects very hard, which is why we need new tools, like AI-driven decision-making systems, to handle their complexity and changeability.

2.2 The role of analysis and prioritization

The initial stages of smart city projects are crucial for setting the groundwork for their success. These stages involve detailed analysis and strategic prioritization to manage the inherent complexities of these projects. Effective resource allocation is one of the primary objectives during this phase. Smart city projects often operate under stringent budget constraints, tight timelines, and limited human resources, necessitating careful planning to optimize these elements. Balancing these factors ensures that the project remains on track and delivers value within the allocated resources.

Goal setting is another essential activity during the initial stages. It involves defining clear, measurable deliverables that align with the needs and expectations of stakeholders. Given the diverse nature of stakeholders in smart city projects—ranging from public authorities to private entities and citizens—it is imperative to establish objectives that balance these varied interests. Clear goals not only provide direction to the development team but also foster a shared understanding among all parties involved, reducing the likelihood of misalignment or conflict as the project progresses.

Prioritization plays a pivotal role in managing the complexity and scope of smart city projects. It entails identifying the most critical features and functionalities for development, enabling teams to focus on high-impact areas during initial iterations. This activity requires an iterative approach to adapt to evolving requirements and stakeholder feedback. By prioritizing, we direct resources towards aspects of the project that deliver the greatest value early on, thereby enhancing stakeholder satisfaction and project credibility [6].

These foundational activities demand a blend of skills typically associated with Product Owners (POs), Business Analysts (BAs), and Product Managers (PMs). While SCRUM frameworks focus on the PO role, the unique challenges of smart city projects necessitate the inclusion of BA and PM competencies. These additional skills enhance the team’s capacity for strategic planning, stakeholder analysis, and goal alignment, filling gaps not explicitly addressed within traditional SCRUM roles. By embedding these roles or skills within the development team, smart city projects can achieve a more structured and effective approach to initial analysis and prioritization.

3. Distribution of activities across three configurations

The distribution of responsibilities and activities within SCRUM teams varies significantly depending on the team configuration and project complexity. In smart city projects, this distribution becomes even more critical due to the multifaceted nature of these initiatives, involving a mix of technical, administrative, and societal dimensions. Each configuration—

whether it involves a sole Product Owner (PO), a PO supported by a Business Analyst (BA), or a full team with a PO, BA, and Product Manager (PM)—has distinct advantages and challenges. The effectiveness of activity distribution directly impacts the team's ability to manage complexity, maintain clear communication with stakeholders, and deliver a successful project. Tailoring the distribution to the specific demands of a smart city project ensures that each role contributes optimally to the overall objectives.

3.1. Key activities in analysis, prioritization, and planning

The early phases of a smart city project are marked by several interconnected activities that lay the foundation for its successful execution. These activities require precise coordination and careful consideration of stakeholder needs, technical feasibility, and project constraints.

The key tasks involved include stakeholder analysis, where diverse groups such as public authorities, private enterprises, and end-users are identified and their expectations understood; defining project goals, which translates stakeholder needs into clear and actionable deliverables; gathering and documenting requirements, a process that captures technical, functional, and performance needs to guide development; creating the product roadmap, a strategic plan that outlines milestones, deliverables, and timelines; prioritizing the product backlog, ensuring that the most impactful and urgent tasks are addressed first; and monitoring progress and prototyping, which involves iterative testing and refinement to align outcomes with objectives. Together, these activities ensure a structured and adaptive approach to managing the complexities of smart city projects.

Smart city projects typically involve a diverse group of stakeholders, including government bodies, private enterprises, and end-users. Conducting a thorough stakeholder analysis is essential to identify their priorities, expectations, and potential contributions. Understanding stakeholder dynamics enables the team to mediate differing objectives and build a consensus-driven approach, ensuring smoother project implementation.

Establishing clear and actionable goals is critical for aligning the team’s efforts with the broader objectives of the project. This step involves translating stakeholder requirements into tangible deliverables, ensuring that all team members and collaborators share a common understanding of the desired outcomes. In smart city projects, goals often encompass technical achievements, societal benefits, and long-term sustainability.

Requirement gathering is a collaborative effort that bridges the gap between stakeholders’ needs and technical possibilities. It involves eliciting detailed input on functionalities, constraints, and performance expectations. Proper documentation of these requirements ensures transparency and serves as a reference throughout the development process, reducing the risk of misunderstandings or scope creep.
The product roadmap provides a strategic vision for the project's development. It outlines the key milestones, deliverables, and timelines, offering a high-level perspective on how the project will progress. For smart city projects, the roadmap must balance innovation with feasibility, addressing both immediate needs and long-term objectives.

Prioritization is crucial to ensure that the most critical features are addressed early in the development cycle. By ranking backlog items based on factors such as stakeholder impact, technical complexity, and resource availability, the team can focus on delivering maximum value at each iteration. This activity is particularly important in smart city projects, where resource allocation and citizen impact are closely scrutinized.

In smart city projects, healthcare services exemplify the critical need for thorough analysis and prioritization during the planning phase. As IoT-based solutions become integral to urban environments, their successful implementation hinges on effectively identifying and addressing stakeholder needs, technical constraints, and resource allocation. Fig. 1 illustrates a conceptual model of smart healthcare services built on the Internet of Things (IoT) [6].

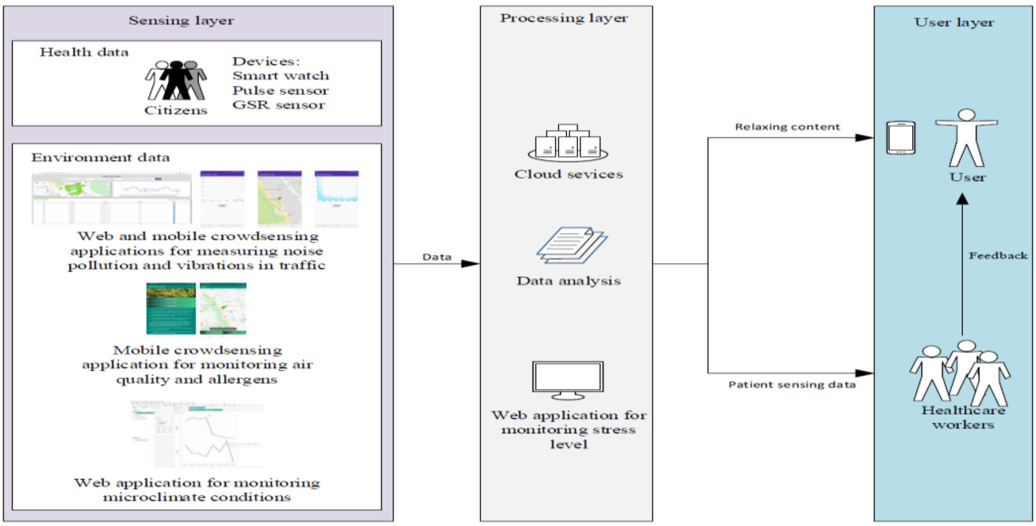

Fig. 1. Model of smart healthcare services based on the Internet of Things.
Source: An IoT System for Healthcare in the Smart City [6].

This model demonstrates how interconnected devices, real-time data analysis, and user-centric interfaces can be orchestrated to deliver high-quality healthcare services. By emphasizing the integration of IoT architectures during the initial planning stages, this figure highlights the importance of defining clear objectives and aligning priorities to address both functional and societal goals in complex smart city projects.

Continuous monitoring of project progress and iterative prototyping are vital to maintaining alignment with goals and stakeholder expectations. Prototyping enables the team to test concepts and gather feedback early, allowing for adjustments before full-scale implementation. This approach minimizes risks and enhances the overall quality of the final product, which is especially important in the context of complex, high-impact smart city projects.

3.2. Role distribution definition for 3 different cases

The following table illustrates how key activities in smart city projects are distributed across three configurations of SCRUM team roles. The table compares 17 activities crucial to smart city project initialization—user research, competitive analysis, defining the product vision, defining problems, ideation, product development strategy, stakeholder management, roadmap creation, product prototyping, defining user journeys, defining epics or features, defining stories, setting acceptance criteria, backlog prioritization, managing sprints, user testing, and training—and shows which team member(s) are responsible for each activity in the three configurations.

Table 1. Distribution of Activities among PO, BA, and PM in Different Scenarios

Activity	Case 1: PO as BA	Case 2: PO + BA	Case 3: PO + BA + PM
User Research	Rarely	PO+BA	PO+BA
Competitive analysis	PO	PO	PO
Product Vision	The client	The client	The client + PM
Define problem	PO	PO	PO
Ideation	Rarely	PO	PO
Product Dev Strategy	The client	The client	The client + PM
Stakeholder Management	PO	PO	PM
Roadmap	PO	PO	PM
Product Prototyping	Rarely	BA	BA
Define user journeys	PO	BA	BA
Define Epics / Features	PO	BA	BA+PO
Define stories	PO	BA	BA
Define acceptance criteria	PO	BA	BA
Backlog prioritization	PO	PO	PO
Managing sprints	PO	PO	PM
User testing	Rarely	BA	BA+PO
Training	Rarely	PO	PO

Source: Authors

In Case 1 the Product Owner (PO) acts as both PO and Business Analyst (BA). In this case, the PO assumes all responsibilities, combining strategic and analytical duties. The PO is responsible for activities such as stakeholder management, defining problems, creating the roadmap, and backlog prioritization, while tasks like user research, product prototyping, and training are rarely addressed.

In Case 2 the PO is supported by a dedicated BA. In this case, the BA shares the workload, particularly for activities like gathering requirements, defining user journeys, and conducting user testing, which require detailed analysis and documentation. The BA also takes responsibility for product prototyping and defining acceptance criteria, enhancing the depth of analytical tasks. However, high-level strategic responsibilities, such as managing the product vision or development strategy, remain unaddressed.

In Case 3 the PO, BA, and a Product Manager (PM) collaborate to fulfill the project requirements. In this case, the inclusion of a PM allows for further division of labor, with the PM taking a leadership role in defining strategic goals, managing the product vision, development strategy, and overseeing stakeholder management, while the BA and PO manage detailed execution. The BA handles user journeys, epics, and acceptance criteria, and the PO focuses on backlog prioritization.

3.3. Analysis of the 3 role distribution cases

Each configuration reflects varying levels of role specialization and team complexity, highlighting their suitability for different project scenarios.

Case 1: PO as BA:

In this configuration, the Product Owner (PO) takes on all responsibilities, including those typically managed by a Business Analyst (BA). It is most suitable for small-scale or less complex projects with limited scope and minimal stakeholder diversity. The centralized structure allows the PO to handle tasks such as stakeholder management, defining problems, creating the roadmap, and backlog prioritization. However, activities like user research, product prototyping, and training are rarely addressed, leading to potential gaps in analytical rigor.

This approach can be efficient for straightforward tasks but poses significant risks of overloading the PO, resulting in inefficiencies in critical activities requiring in-depth analytical expertise, such as gathering requirements and monitoring progress. While it may suffice for simpler projects, its limitations become apparent as complexity increases.

Case 2: PO + BA:

The inclusion of a dedicated Business Analyst (BA) in this setup enables better workload distribution, particularly for tasks that are documentation- and analysis-heavy. The BA assumes responsibility for activities such as gathering requirements, defining user journeys, product prototyping, and setting acceptance criteria, while the PO focuses on strategic alignment and backlog prioritization.

This configuration balances efficiency with analytical depth, making it well-suited for medium-complexity projects. However, the absence of a Product Manager (PM) limits its capacity for strategic oversight, particularly in areas like managing the product vision and development strategy, which might be critical in projects requiring extensive stakeholder alignment or long-term planning.

Case 3: PO + BA + PM:

This configuration offers the highest level of specialization, incorporating a Product Manager (PM) alongside the PO and BA. The PM assumes responsibility for strategic oversight, such as defining project goals, managing the product vision, development strategy, and overseeing stakeholder management. Meanwhile, the BA focuses on analytical tasks, such as defining user journeys, epics, and acceptance criteria, and the PO handles backlog prioritization and tactical execution.

This setup ensures a clear delineation of responsibilities, allowing each role to focus on its core competencies. It is ideal for complex projects involving diverse stakeholders and extensive requirements, enhancing team efficiency and providing a focused approach to managing the multifaceted demands of smart city initiatives.

Overall, the analysis emphasizes the critical importance of tailoring role distribution to the specific needs and complexities of a project. While Case 1 may suffice for simpler initiatives with limited scope and stakeholder involvement, the additional expertise introduced in Cases 2 and 3 significantly enhances the team's capacity to address the multifaceted challenges of smart city projects.

4. Machine learning model for team optimization

The proposed ML model assists in optimizing SCRUM team configurations by analyzing project-specific characteristics and leveraging historical data. The model provides a data-driven approach to address the varying demands of smart city projects. AI-driven solutions are increasingly recognized for their potential to optimize decision-making in public organizations and smart city initiatives [7].

4.1. Inputs and architecture of the ML model

The ML model uses a supervised classification approach, such as Random Forest or Gradient Boosting, to process inputs and generate recommendations. The primary inputs include:

- Project complexity: factors, such as scope, stakeholder diversity, and technological integration.
- Stakeholder diversity: the number and the type of stakeholders involved, from local authorities to private entities and end-users.
- Resource constraints: budget, time, and team size limitations.
- Historical success metrics: data from past projects, including team performance, delivery timelines, and stakeholder satisfaction.

The model architecture employs supervised classification algorithms, such as Random Forest or Gradient Boosting, to process these inputs. These algorithms are well-suited for handling structured data and identifying patterns to predict optimal configurations [8]. The architecture incorporates these inputs into a feature set that is fed into the classification algorithm.

Training data is derived from a mix of quantitative surveys from over 50 professionals and qualitative insights from expert interviews. The model employs k-fold cross-validation to ensure robustness and accuracy, reducing the risk of overfitting and improving generalizability.

Decision-making in smart city projects requires a structured and iterative approach, particularly when integrating machine learning solutions for team optimization. Fig. 2 illustrates a multi-step model of the decision-making process that involves defining objectives, gathering relevant data, analyzing alternatives, and selecting the optimal solution [9]. This model provides a conceptual foundation for the architecture of the proposed machine learning model.

By incorporating similar iterative steps, the machine learning model ensures that inputs such as project complexity, stakeholder diversity, and resource constraints are systematically analyzed to recommend the most suitable SCRUM team configuration. The multi-step approach depicted in the figure underlines the importance of data-driven and goal-oriented methodologies, which are crucial for navigating the multifaceted challenges of smart city initiatives.

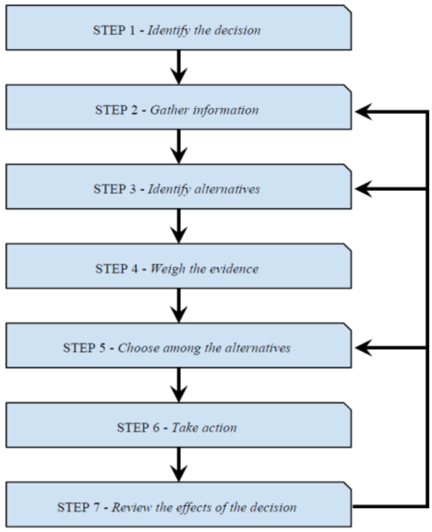

Fig. 2. Multi-step Decision-Making Model for Smart City Management.
Source: Smart City Management based on IoT [9].

Digital twins play a crucial role in enhancing decision-making by enabling real-time simulations and predictive analysis of urban systems. By integrating IoT data and analytics, they allow city planners to evaluate scenarios, anticipate challenges, and implement data-driven solutions effectively [10].

Similarly, the digitalization of public administration supports structured decision-making processes, improving transparency, resource allocation, and stakeholder collaboration, aligning with broader European trends [11].

4.2. Implementation and outputs of the ML model

The implementation process includes the following steps:

- Data collection and preprocessing: empirical data from surveys and expert interviews are organized into a structured dataset.
- Algorithm training: a supervised classification approach is used to train the model, focusing on predicting team configurations (Case 1, 2, or 3).
- Validation: K-fold cross-validation ensures the accuracy and robustness of the model, minimizing the risk of overfitting and enhancing its ability to generalize across various scenarios.

The model generates outputs in the form of recommendations for team structures:

- Case 1: Recommended for projects with low complexity, limited scope, and minimal stakeholder involvement.

- Case 2: Suggested for medium-complexity projects where balanced analytical and strategic oversight is needed.
- Case 3: Optimal for high-complexity initiatives requiring specialized roles for strategic planning, execution, and stakeholder management.

For example, for a medium-complexity project with diverse stakeholders, the model may recommend Case 2 (PO + BA) as the most efficient configuration, balancing resource constraints with skill distribution. In contrast, a large-scale government-level project would likely necessitate Case 3 (PO + BA + PM) to address the multifaceted demands effectively.

The proposed ML model offers several significant benefits for smart city project management. First, it reduces decision-making time for project managers by providing data-driven recommendations for team configurations, allowing them to focus on higher-level strategic objectives.

Second, it improves project outcomes by aligning team roles and responsibilities with the specific requirements of the project, ensuring that resources are utilized effectively and stakeholder expectations are met.

Finally, the model is highly scalable, capable of supporting a wide range of project complexities—from localized smart city initiatives, such as urban mobility applications, to nationwide systems, such as comprehensive traffic management platforms. This adaptability makes it a valuable tool for optimizing team structures across diverse project scenarios.

5. Conclusions and future directions

This study highlights the importance of proper team configuration in smart city projects, emphasizing the foundational role of analysis and prioritization. By addressing the gaps in SCRUM's standard role definitions and integrating a machine learning-based tool, the paper provides a scalable and efficient solution for optimizing team structures. Future work will explore expanding the model to other agile frameworks and validating its applicability in non-smart city domains.

The proposed model successfully bridges the gap between traditional SCRUM frameworks and the unique demands of smart city initiatives, which often involve diverse stakeholders, scalability challenges, and significant socio-technical complexities. The findings underscore the necessity of tailoring team configurations based on project complexity. While Case 1 (PO as BA) proves effective for smaller, less complex projects, Case 2 (PO + BA) and Case 3 (PO + BA + PM) are more suitable for medium and high-complexity initiatives, respectively. This role distribution not only improves team efficiency but also ensures better alignment with stakeholder expectations and project objectives.

Future research can build on this foundation by exploring several critical directions. Expanding the model to other agile methodologies, such as Kanban or SAFe, could provide further insights into the generalizability of machine learning-based team optimization. Additionally, incorporating real-time project performance data into the machine learning model would enhance its predictive accuracy and adaptability to changing conditions. Validating the model's applicability in domains beyond smart cities, including healthcare, education, and manufacturing, could demonstrate its versatility and broader impact.

Furthermore, addressing ethical considerations in AI-driven decision-making, such as privacy, bias, and stakeholder inclusivity, remains an essential area for future investigation. In conclusion, this study contributes to the growing body of knowledge on the intersection of artificial intelligence and agile project management, particularly in the context of smart cities. By leveraging the insights gained from this research, practitioners and academics can develop more efficient, scalable, and adaptive approaches to managing complex software projects, ensuring successful outcomes in dynamic and multifaceted environments.

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