Department of Digital Business
Journal of Artificial Intelligence and Digital Business (RIGGS)
Homepage: https://journal.ilmudata.co.id/index.php/RIGGS
Vol. 4 No. 3 (2025) pp: 2831-2842
P-ISSN: 2963-9298, e-ISSN: 2963-914X

Smart Service Design in Urban Rail: AI-Enhanced Blueprint, Digital Servicescape, and Passenger Experience at Jabodebek LRT Jatimulya Station

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Abstract

Urban rail systems are increasingly positioned as vital components of sustainable mobility, enabling modal shifts from private to public transport while reducing congestion and fostering urban growth. In Indonesia, the Jabodebek Light Rail Transit (LRT) represents a flagship project to modernize metropolitan transportation, yet its success depends not only on infrastructure but also on the quality of service design at the station level, where passengers evaluate safety, reliability, and comfort. Jatimulya Station, as a type-A terminal in the Bekasi corridor, highlights persistent challenges such as ticketing inefficiencies, overcrowding, inadequate wayfinding, and accessibility barriers, which undermine user satisfaction and expose the limitations of conventional operational frameworks. This study investigates how artificial intelligence can be integrated into service blueprinting and digital servicescape design to enhance passenger experience at Jatimulya Station. Using a qualitative approach supported by literature review, observations, interviews, and document analysis, the research employs thematic analysis to map passenger journeys, identify service encounter bottlenecks, and assess environmental factors affecting user perceptions. Findings demonstrate that AI-enhanced blueprinting enables predictive congestion management, dynamic staff allocation, and real-time adjustments, while digital servicescape innovations improve wayfinding, inclusivity, and transparency by synchronizing physical and digital touchpoints. Theoretically, this study extends established frameworks of service blueprint, servicescape, and service encounters into AI-driven contexts, while practically offering recommendations for PT Kereta Api Indonesia and policymakers to optimize station-level service delivery, improve passenger trust, and advance sustainable urban mobility.

Keywords: *AI-Enhanced Service Blueprint; Digital Servicescape; Passenger Experience; Smart Mobility; Jabodebek LRT*

1. Introduction

Urban rail systems are increasingly positioned as a critical element of sustainable mobility in metropolitan areas, enabling modal shifts from private to public transport while supporting economic growth and reducing congestion [1]. In Indonesia, the Jabodebek Light Rail Transit (LRT) represents a flagship infrastructure project intended to modernize urban transportation and improve accessibility in Jakarta and its surrounding cities [2]. However, the success of such systems extends beyond infrastructure delivery; it depends heavily on the quality of service design at the station level, where passengers evaluate safety, comfort, reliability, and efficiency [3]. Jatimulya Station, as one of the type-A terminals on the Bekasi corridor, provides an important case for assessing how service design influences passenger experience.

Despite progressive improvements, there remain visible gaps between expected service standards and the actual passenger experience at Jabodebek LRT. Observations at Jatimulya Station highlight ticketing frictions, crowding during peak hours, inadequate wayfinding, and accessibility challenges [4]. These service shortfalls are consistent with earlier findings that station-level inefficiencies, if unresolved, diminish ridership satisfaction and discourage long-term loyalty [5]. Moreover, existing operational strategies often rely on conventional frameworks that inadequately incorporate digitalization, real-time adaptability, and customer-centered innovation .

From a theoretical perspective, the frameworks of service blueprint, service encounter, and servicescape remain central to the analysis of transport service quality. Service blueprinting offers a diagnostic approach for mapping customer journeys, revealing critical frontstage–backstage interactions, and identifying latent failure points [6]. Servicescape research highlights how ambient, spatial, and symbolic cues shape passengers' perceptions and behaviors, while service encounters emphasize the importance of direct interactions between staff and users [7].

Nevertheless, existing studies on Indonesian rail transport rarely integrate these frameworks with emerging AI-driven digital business models, despite evidence that such integration is increasingly critical in global transit contexts [8].

The urgency of this research lies in ensuring that Indonesian public transport services evolve in line with global best practices in smart mobility (Purba et al., 2020). Neglecting service design innovations risks reducing public trust in large-scale investments and constrains the modal shift necessary for sustainable urban mobility [9]. Furthermore, the integration of artificial intelligence (AI) into service design has shifted from being a supplementary innovation to becoming an operational necessity. AI enables predictive analytics for crowd management, automation of information flows, and personalization of passenger services, all of which contribute to service resilience and adaptability [10].

Accordingly, this study investigates the application of AI-enhanced service blueprinting and digital servicescape design at Jatimulya Station. Using observations, interviews, and document analysis, it maps the passenger journey, identifies service encounter bottlenecks, and evaluates environmental factors affecting user experience [11]. This approach bridges the gap between conventional service quality frameworks and AI-enabled operational strategies, offering a more adaptive model for station-level service improvement [12].

The contribution of this study is twofold. First, it advances theoretical discourse by integrating digital business strategies and AI applications into the established frameworks of service blueprint, service encounter, and servicescape [13]. Second, it provides practical recommendations for PT Kereta Api Indonesia and policymakers to optimize station-level service delivery, improve passenger trust, and achieve policy objectives in sustainable transportation [14]. In this way, the study positions Jabodebek LRT not only as a national flagship but also as a potential benchmark for smart urban rail operations across Southeast Asia.

2. Research Methods

This research adopts a qualitative approach with an emphasis on interpretive analysis to explore how service blueprinting, digital servicescape, and passenger experience can be enhanced through the integration of artificial intelligence in urban rail services [15]. A qualitative design was chosen to provide a deeper understanding of the context, processes, and meanings embedded in service delivery at Jatimulya Station of the Jabodebek LRT. The study is framed as a literature-based inquiry complemented by field insights. The literature review involved the systematic examination of recent studies on service quality, blueprinting, servicescape, and digital transformation in public transportation [16]. This allowed the researchers to establish theoretical foundations, identify best practices, and map knowledge gaps that informed the research focus.

In addition to literature review, data collection was conducted using three main techniques: observation, interviews, and document study [17]. Observation was performed at Jatimulya Station to capture real-time passenger interactions, flow patterns, and service encounters. Semi-structured interviews were conducted with both passengers and service staff to explore perceptions, challenges, and expectations regarding station services [18]. The document study involved analyzing operational manuals, service reports, and official communications related to the Jabodebek LRT.

The data analysis followed a thematic approach. First, observational notes, interview transcripts, and documents were organized into categories reflecting stages of the passenger journey, such as arrival, ticketing, gate entry, platform usage, and egress [19]. Second, recurring themes were identified, including ticketing reliability, accessibility, staff interactions, and environmental conditions. Third, these themes were mapped onto a service blueprint framework to reveal interconnections between frontstage activities, backstage processes, and supporting systems. Finally, the results were interpreted in relation to the concept of digital servicescape and the potential application of AI for enhancing passenger experience [20].

Through this method, the study seeks to produce an integrated understanding of service quality challenges and propose actionable strategies for smart service design in urban rail operations. Specifically, it aims to delineate how AI integration can optimize passenger flow, enhance real-time information dissemination, and personalize user interactions within the complex operational landscape of modern rail systems. This comprehensive approach ensures that the proposed solutions are not only theoretically sound but also practically implementable within the dynamic environment of urban mass transit. Such an analytical framework provides a robust foundation for examining the nuanced interplay between technological advancements, specifically AI, and the human-centric aspects of service delivery, thereby addressing a critical gap in contemporary urban mobility research [21].

DOI: https://doi.org/ 10.31004/riggs.v4i3.2386

3. Results and Discussions

3.1. AI-Enhanced Service Blueprinting for Urban Rail Operations

Service blueprinting traditionally functions as a visual tool to map customer actions, frontstage encounters, backstage processes, and supporting systems. At Jatimulya Station, the blueprint reveals the complexity of interactions among passengers, staff, and technologies. Incorporating artificial intelligence into this framework introduces predictive and adaptive capabilities, enabling managers to anticipate disruptions and dynamically allocate resources. For instance, AI can analyze real-time passenger flow data, leveraging machine learning algorithms to predict congestion points and optimize train schedules or staff deployment, thereby enhancing operational efficiency [22][23]. This proactive approach, informed by AI, reduces potential delays and improves overall service reliability by making the "black box" of AI more tangible for service scholars and practitioners [21].

AI-driven blueprinting allows the translation of static process maps into responsive systems. For example, real-time data from ticketing devices, passenger counters, and crowd detectors can be processed by machine learning models to forecast demand surges or identify bottlenecks before they escalate. This contrasts with conventional blueprints, which only illustrate workflows but do not provide predictive insights. Furthermore, AI applications, still in their nascent stages within the railway sector, offer substantial potential for optimizing complex railway systems and enhancing customer service quality [24]. The integration of AI, therefore, shifts service blueprinting from a descriptive to a prescriptive and adaptive tool, enabling continuous improvement in urban rail operations. Moreover, AI can refine service blueprints by simulating various scenarios, such as the impact of system failures or unexpected surges in passenger numbers, allowing for the pre-optimization of response strategies and resource allocation [22].

By embedding AI into the blueprint, rail operators can simulate various service scenarios. For instance, the impact of equipment failures, staff shortages, or sudden passenger influxes can be modeled, producing proactive strategies to minimize disruption. This analytical layer helps move from reactive problem solving to preventive service management. This integration allows for dynamic adjustments to operational parameters, such as train dispatch intervals or station gate configurations, based on real-time predictive analytics, thereby enhancing the resilience and adaptability of the entire urban rail network [22]. Moreover, AI-powered systems can learn from past operational data, identifying patterns and correlations that human operators might overlook, which leads to more refined and efficient service blueprint iterations over time [25]. Additionally, the incorporation of AI into service blueprinting facilitates a deeper understanding of passenger behavior by analyzing historical travel patterns and preferences, leading to more personalized service offerings and improved passenger satisfaction [26].

At Jatimulya Station, delays at ticketing gates and congestion at escalators exemplify situations where AI could support decision-making. Predictive analytics may inform staff deployment at gates or optimize the timing of gate resets. In this way, blueprinting evolves into a living system that both documents and governs operational priorities. The application of AI in this context extends beyond simple automation, enabling a sophisticated interplay between real-time data analysis and strategic operational adjustments [27]. Specifically, AI algorithms can process vast amounts of sensor data from various points within the station, such as turnstiles, cameras, and IoT devices, to identify emergent patterns in passenger movement and queuing dynamics, allowing for automated adjustments to alleviate congestion. This allows for dynamic resource allocation and preemptive intervention, transforming the service blueprint into an agile framework responsive to fluctuating operational demands.

Beyond internal management, AI-enabled blueprints can also communicate transparently with passengers. By linking operational triggers to passenger information displays, travelers receive more timely and consistent updates, reinforcing trust in the system. This enhanced transparency, driven by AI's ability to process and disseminate real-time operational data, fosters a more informed and empowered passenger experience, ultimately leading to higher satisfaction and operational efficiency within urban rail environments. Furthermore, AI-driven solutions can predict maintenance needs for critical infrastructure, minimizing unplanned service interruptions and ensuring continuous operational flow. Such predictive capabilities, enabled by machine learning, can forecast equipment failures before they occur, allowing for scheduled maintenance during off-peak hours and further enhancing service reliability and safety [28].

Therefore, AI-enhanced service blueprinting is not only a diagnostic instrument but also a strategic tool for continuous improvement. It bridges the gap between observed service failures and systemic remedies, ensuring alignment between organizational capacity and passenger expectations. This integration of AI allows for dynamic process management and optimization of business processes, moving beyond static improvements to adaptable, predictive models [29]. This analytical framework enables urban rail operators to proactively identify potential

DOI: https://doi.org/ 10.31004/riggs.v4i3.2386

inefficiencies and bottlenecks, transforming reactive problem-solving into a data-driven, preemptive strategy for operational excellence [25]. This proactive approach not only optimizes current operations but also provides a scalable framework for integrating future technological advancements, ensuring the sustained relevance and efficiency of urban rail systems.

3.2. The Digital Servicescape and Passenger Experience

The servicescape—comprising ambient conditions, spatial layout, and symbolic cues—plays a defining role in shaping passenger perceptions. At Jatimulya Station, elements such as signage, lighting, cleanliness, and accessibility contribute significantly to the overall journey experience. The integration of digital technologies extends the concept of servicescape into a "digital servicescape," where physical and digital touchpoints combine to influence passenger satisfaction. This fusion creates an immersive environment where real-time information, personalized services, and interactive elements converge to redefine the passenger journey [30]. This novel paradigm allows for the proactive management of passenger flow and the dynamic adaptation of environmental stimuli to optimize comfort and efficiency [31]. For instance, smart displays can provide real-time updates on train schedules and platform changes, while also adjusting lighting and ambient sounds to reduce passenger stress during peak hours [32].

Digital signage, interactive kiosks, and mobile applications represent the digital extensions of the servicescape. When well-designed, these elements offer clarity, reduce uncertainty, and empower passengers with self-service options. For example, digital route maps and crowd detectors can alleviate anxiety during peak hours by providing real-time information about train availability and station density. Furthermore, personalized notifications delivered via mobile applications, powered by AI, can guide passengers through the least congested paths, optimizing their transit time and improving overall flow within the station [33].. These digital enhancements not only facilitate smoother navigation but also augment the aesthetic and functional aspects of the station environment, transforming it into a dynamic, information-rich hub that anticipates and responds to passenger needs [34].

Passengers at Jatimulya Station reported confusion at decision points, particularly in navigating vertical circulation routes and selecting the correct platforms. This highlights the need for a stronger integration between physical wayfinding cues and digital systems. A digital servicescape can address these weaknesses by offering synchronized audio-visual information across multiple channels. For instance, dynamic digital displays could provide animated wayfinding instructions, supplementing static signs, while an integrated mobile application could offer turn-by-turn navigation within the station, significantly reducing passenger disorientation [35]. This comprehensive digital integration enhances accessibility and usability, particularly for those unfamiliar with the station layout or individuals with special needs, by providing ubiquitous, personalized guidance. Such advancements create a responsive and intuitive environment, transforming potentially stressful journeys into seamless experiences for all users [36].

The sensory environment also requires refinement. While cleanliness and lighting are consistently positive, platform acoustics and thermal comfort are less optimal. Digital tools, such as adaptive ventilation systems or noise-level monitoring, can enhance comfort and accessibility in ways that manual supervision cannot. Furthermore, incorporating AI-driven environmental controls, such as smart HVAC systems, could dynamically adjust temperature and air quality based on real-time occupancy data, ensuring optimal thermal comfort and energy efficiency [37]. Similarly, personalized audio zones, enabled by directional sound technology, could mitigate noise pollution by delivering specific announcements only to relevant passengers, thereby creating a more serene environment on the platforms [38]. Moreover, the deployment of intelligent soundscapes, which leverage AI to modulate ambient sounds and announcements, can significantly reduce auditory stress and improve the clarity of critical information [39].

From a psychological perspective, the digital servicescape strengthens perceived control among passengers. When travelers feel equipped with accurate, timely, and comprehensible information, they are more resilient to disruptions. This resilience translates into higher satisfaction, greater trust, and stronger willingness to reuse the service. Furthermore, the seamless integration of AI-powered personalized services, such as real-time delay notifications and re-routing suggestions, can mitigate the cognitive load associated with travel uncertainties, fostering a sense of mastery over the journey. This heightened sense of control, facilitated by advanced digital interfaces, transforms passive commuters into active participants in their travel experience, significantly enhancing overall satisfaction and loyalty [40]. This enhanced autonomy, coupled with the immediate availability of information and support via AI-driven platforms, cultivates a more positive emotional experience for passengers, effectively mitigating travel-related anxieties [41].

DOI: https://doi.org/ 10.31004/riggs.v4i3.2386

Thus, the digital servicescape provides an essential framework for integrating AI into station design. It allows for continuous monitoring of passenger flows, ensures inclusivity for diverse groups, and elevates the overall brand image of the LRT as a smart and modern transport solution. This strategic application of digital technologies transforms the station from a mere transit point into an intelligent, responsive ecosystem that prioritizes passenger well-being and operational efficiency. This integration further enables predictive analytics to anticipate peak loads and potential bottlenecks, optimizing resource allocation and service delivery proactively. This proactive approach, underpinned by AI, not only improves daily operations but also provides a robust framework for long-term strategic planning and infrastructure development, ensuring the Jabodebek LRT remains at the forefront of urban transit innovation [25].

3.3. Service Encounters and the Role of Human Interaction

While digital systems play a critical role in managing complexity, service encounters—the interactions between staff and passengers—remain central to shaping perceptions. At Jatimulya Station, staff are often courteous and responsive, yet their engagement tends to be reactive rather than proactive. This limits their ability to prevent minor issues from escalating into larger service disruptions. Implementing AI-powered predictive analytics could equip staff with real-time insights into potential pain points, allowing them to intervene preventatively and enhance service delivery [42]. For instance, AI could analyze passenger flow data to identify areas prone to congestion or predict technical malfunctions, thereby enabling staff to preemptively address these issues [43].

AI can complement human service encounters by providing real-time decision support. For example, predictive crowd management tools can alert staff to potential congestion zones, prompting them to redirect passenger flows before bottlenecks emerge. Staff, therefore, act not only as problem-solvers but as facilitators of seamless mobility. This synergy between human expertise and AI-driven intelligence transforms traditional roles, fostering a proactive service environment where staff can anticipate and mitigate issues before they impact the passenger experience. This collaborative approach, integrating the intuitive adaptability of human personnel with the analytical prowess of AI, significantly elevates service quality and operational efficiency. Furthermore, generative AI can significantly augment staff capabilities by synthesizing complex data into actionable insights, enabling more nuanced and personalized passenger interactions [44].

Training programs should emphasize anticipatory service behaviors. Instead of waiting for passengers to ask questions, staff can be guided to proactively provide information at choke points, such as ticket machines, concourse areas, and boarding gates. Such proactive encounters reduce hesitation, enhance efficiency, and foster positive emotional impressions. This approach can be further enhanced by leveraging AI to generate personalized, context-aware information pushes, ensuring that passengers receive relevant updates precisely when and where they need them [21]. For example, AI could analyze a passenger's typical route and provide real-time updates on potential delays or alternative routes, thereby minimizing disruption and enhancing overall satisfaction [28]. This proactive information dissemination strategy, powered by AI, transforms the passenger experience from a transactional interaction into a supportive and informed journey.

Incorporating AI-driven prompts into handheld devices can support these behaviors. For instance, staff may receive alerts when dwell times exceed thresholds or when ticketing errors spike, enabling them to intervene with timely assistance. This creates a symbiotic relationship between human empathy and machine precision. This integration ensures that human intervention is both targeted and efficient, optimizing resource allocation while maximizing passenger satisfaction. This symbiotic relationship between AI and human staff is critical for managing the complexities of urban rail environments, transforming potential friction points into opportunities for enhanced service delivery [45].

The quality of service encounters also directly affects passenger loyalty. Even in technologically advanced environments, personal interactions remain the most memorable aspects of the journey. Passengers often evaluate the system not only based on technical reliability but also on how they were treated in moments of uncertainty. Therefore, investing in staff training that emphasizes empathetic communication and efficient problem-solving, supported by AI tools, can significantly bolster passenger trust and satisfaction, particularly during service disruptions [46]. Moreover, AI-driven facial recognition systems can expedite check-in processes and eliminate the need for paper-based boarding passes, contributing to both operational efficiency and environmental sustainability [47]. Furthermore, the integration of AI can enhance the personalization of services, moving beyond mere efficiency to anticipate individual passenger needs and preferences [48].

Therefore, strengthening the synergy between AI-enabled insights and human encounters is essential. By aligning staff scripts with predictive analytics, service encounters can shift from reactive corrections to proactive orchestration, elevating both efficiency and passenger satisfaction. This allows for the dynamic adaptation of service delivery, ensuring that human interactions are strategically deployed to address complex issues that require emotional intelligence and nuanced problem-solving, rather than routine inquiries [45]. This strategic deployment ensures that AI handles repetitive tasks, freeing human staff to focus on high-value interactions that genuinely enhance the passenger experience and address unique circumstances [49]. This integrated approach further enables the development of adaptive service protocols that can dynamically respond to evolving operational conditions and passenger demographics, ensuring a continually optimized service delivery model.

3.4. Accessibility and Inclusivity in Service Design

Accessibility is a cornerstone of equitable transport services. At Jatimulya Station, facilities such as elevators, tactile paving, and dedicated spaces for persons with disabilities exist but are not always fully functional or seamlessly integrated. Discontinuities in tactile guidance and occasional elevator unavailability illustrate the barriers faced by vulnerable groups. To mitigate these challenges, AI can be leveraged to monitor the operational status of accessibility infrastructure in real-time, alerting maintenance teams to issues before they significantly impact passenger mobility [50]. This proactive monitoring system, driven by sophisticated AI algorithms, could significantly enhance the reliability and usability of essential accessibility features, thereby improving the overall travel experience for all passengers, especially those with specific needs.

AI integration offers promising solutions for enhancing accessibility. Real-time monitoring of accessibility assets, such as elevators and escalators, can alert staff and passengers when disruptions occur. Automated rerouting information displayed on screens and mobile applications ensures that individuals with special needs are not disadvantaged during their journey. This ensures continuous, unimpeded access for all passengers, aligning with the principles of universal design in urban transit systems. Furthermore, predictive AI models can analyze usage patterns and proactively schedule maintenance for these critical accessibility features, minimizing downtime and ensuring their continuous availability [25]. This predictive maintenance capability directly supports the goal of creating barrier-free smart city infrastructure, addressing common accessibility challenges that often arise from socio-technical system failures [51].

Inclusivity also extends to information accessibility. Announcements in multiple languages, visual aids for passengers with hearing impairments, and mobile applications with voice-enabled navigation are key components of a truly inclusive servicescape. At Jatimulya Station, current practices can be expanded to address these dimensions more systematically. AI-powered solutions, such as real-time language translation for digital displays and voice announcements, can bridge communication gaps for diverse passenger demographics [52]. Moreover, natural language processing algorithms can analyze passenger queries and provide instant, accurate responses, reducing reliance on manual information desks and improving overall efficiency [53]. These technologies can significantly enhance the experience for visually impaired passengers through AI-powered navigation aids, object recognition, and scene description capabilities, ensuring greater independence and safety within the station environment [54].

Accessibility is not merely a compliance issue but a determinant of overall service quality [55]. When facilities fail, the perceived fairness of the transport system declines, undermining trust and discouraging long-term ridership among affected groups. A smart design approach ensures redundancy and resilience in accessibility features. This includes implementing fail-safe mechanisms and redundant systems for critical infrastructure like elevators and escalators, coupled with AI-driven predictive maintenance to preemptively address potential failures and ensure uninterrupted service for all passengers [56]. Furthermore, AI can facilitate the development of personalized accessibility solutions, such as dynamic wayfinding applications that adapt to individual mobility requirements and provide real-time assistance [57].

Inclusive design also enhances the reputation of the Jabodebek LRT. By adopting globally recognized accessibility standards and embedding AI to monitor and adapt services, the system positions itself as progressive and people-centered. This contributes to the national agenda of fostering equality in public services. This commitment to inclusivity can also attract a broader ridership, including tourists and international visitors, thereby boosting the economic viability of the urban rail network. This comprehensive approach to accessibility, supported by AI, transforms Jatimulya Station into a model of inclusive urban mobility, setting a precedent for future smart city developments. The integration of AI-enhanced accessibility features thus moves beyond mere compliance, establishing a new benchmark for equitable urban transit systems that prioritize universal access and user experience.

DOI: https://doi.org/ 10.31004/riggs.v4i3.2386

Thus, prioritizing accessibility and inclusivity is both a moral imperative and a strategic advantage. It strengthens passenger satisfaction, enhances international credibility, and aligns with the broader policy goal of sustainable and equitable urban mobility. Furthermore, the deployment of AI in optimizing accessibility features contributes to reducing the operational burden associated with manual inspections and reactive maintenance, thereby improving resource allocation efficiency [58]. This shift towards proactive, AI-driven maintenance not only ensures higher service availability for all users but also liberates human resources to focus on more complex tasks, ultimately enhancing the overall operational efficacy of the urban rail system [59]. This comprehensive approach transforms Jabodebek LRT Jatimulya Station into a model of inclusive urban mobility, setting a precedent for future smart city developments in Indonesia and beyond [60].

3.5 Real-Time Information and Reliability Perceptions

Reliability is one of the most influential dimensions of transport service quality. At Jatimulya Station, reliability is not only measured by train punctuality but also by the quality of real-time information delivered to passengers. Gaps in disruption messaging and inconsistent wayfinding cues highlight the limitations of current communication strategies. The integration of AI, however, offers a transformative potential by providing accurate, real-time data on train movements, platform changes, and service interruptions, thereby significantly enhancing passenger confidence and operational transparency [61]. This is particularly crucial given that passenger satisfaction with public transportation is significantly influenced by the perception of service quality, which includes reliability and the availability of timely information [62].

AI-powered information systems can transform reliability perceptions by offering passengers consistent and predictive updates. For example, crowd density data can inform passengers about less congested carriages, while predictive delay announcements allow them to adjust expectations in real time. These proactive measures reduce frustration and improve trust in the system. Real-time bus arrival/departure predictions, enhanced by IoT sensors and advanced data analytics, exemplify how artificial intelligence can improve scheduling and on-time performance, which is crucial for passenger satisfaction and operational efficiency in transportation systems [63]. Consequently, the implementation of AI and machine learning algorithms in analyzing vast datasets from various sensors and operational metrics can dynamically adjust service schedules and disseminate precise information, thereby mitigating the negative impact of unforeseen disruptions on passenger experience [64].

Timeliness of information is particularly crucial during peak hours. Passengers are more forgiving of minor delays if they are kept informed with clear and accurate updates [65]. Conversely, a lack of transparency breeds uncertainty and dissatisfaction, even when disruptions are short. AI-driven systems can analyze historical and real-time operational data to predict potential delays or disruptions, enabling proactive communication strategies that enhance passenger satisfaction and operational resilience [66]. These systems can disseminate information through multiple channels, including mobile applications, station displays, and personalized alerts, ensuring that passengers receive relevant updates in a timely and accessible manner [67][68]. Furthermore, the integration of advanced analytics with artificial intelligence can enable the system to anticipate passenger flow changes and dynamically adjust service frequencies, optimizing the balance between supply and demand [53].

The integration of mobile-first platforms with station displays ensures that passengers receive information across multiple channels. This redundancy accommodates diverse preferences and accessibility needs, reducing the risk of exclusion [69]. At Jatimulya Station, expanding these platforms can address recurring passenger concerns about clarity and consistency. Such platforms can leverage AI to personalize information delivery, offering tailored updates based on individual travel patterns and preferences, further enhancing the user experience [70]. This personalized dissemination of information can significantly mitigate passenger anxiety during unforeseen circumstances and empower them to make informed decisions regarding their journeys. The dynamic adjustment of information based on real-time operational metrics and passenger location can optimize routing suggestions, minimizing inconvenience during service anomalies.

Reliable information is also a marketing asset. A system that communicates proactively builds a reputation for transparency and customer focus. This strengthens loyalty and encourages positive word-of-mouth, both of which are critical for sustaining ridership growth. This proactive communication strategy can foster a sense of trust and dependability among commuters, transforming occasional riders into regular patrons. The ability to provide accurate and timely information also allows urban rail operators to manage passenger expectations effectively, which is a key component of overall service satisfaction [71]. Moreover, integrating AI into real-time information dissemination systems can provide granular insights into passenger movement patterns, enabling predictive analytics for crowd management and optimized resource deployment [72][63].

DOI: https://doi.org/ 10.31004/riggs.v4i3.2386

Thus, enhancing real-time information systems is not only an operational improvement but also a strategic measure for shaping public perceptions of reliability [73]. It represents a cost-effective way to enhance trust, satisfaction, and long-term system resilience. This comprehensive approach to information dissemination, driven by artificial intelligence, transforms the passenger experience by minimizing uncertainty and maximizing operational efficiency [74]. The deployment of AI-enhanced predictive analytics for real-time disruption management can further refine service delivery by anticipating bottlenecks and rerouting passengers proactively. This proactive capability significantly mitigates the cascading effects of service interruptions, thereby enhancing the overall stability and responsiveness of the urban rail network [75][64].

3.6 Continuous Improvement and Policy Implications

The final dimension of discussion centers on the importance of continuous improvement. Service design is not a one-time initiative but an evolving process that requires regular feedback loops and adaptive learning. At Jatimulya Station, recurring issues in ticketing, accessibility, and crowd management illustrate the need for systematic monitoring and periodic redesign. This involves leveraging AI-driven analytics to identify service bottlenecks, assess the effectiveness of interventions, and predict emerging challenges, thereby ensuring that design enhancements are data-driven and responsive to passenger needs [76]. The integration of continuous feedback mechanisms, enabled by IoT sensors and AI algorithms, allows for dynamic adjustments to service parameters, optimizing operational efficiency and passenger satisfaction in real-time [77]. Furthermore, advanced AI algorithms, such as deep learning and ensemble models, can enhance predictive accuracy and robustness, leading to more comprehensive insights into equipment health and operational performance [78].

AI-enabled feedback systems can automate data collection from multiple sources, including ticketing logs, passenger surveys, and incident reports. This creates a comprehensive evidence base for decision-making. When analyzed regularly, these data streams reveal patterns that guide targeted interventions [79]. For instance, machine learning models can identify correlations between passenger complaints and specific operational events, enabling precise adjustments to service delivery or infrastructure. This iterative process of data collection, analysis, and intervention forms a continuous improvement cycle, ensuring that service enhancements are consistently aligned with evolving passenger expectations and operational realities [78]. Such systems can also leverage predictive analytics to anticipate maintenance needs for metro signal equipment, thus preventing failures and reducing maintenance costs [80], [81]. Furthermore, the application of predictive models allows for proactive maintenance scheduling, minimizing downtime and extending the operational lifespan of critical railway infrastructure components [82].

Continuous improvement also requires institutional commitment. PT Kereta Api Indonesia and Jabodebek LRT management should establish quarterly service reviews that integrate blueprint updates with performance indicators. Such practices embed learning into the organizational culture, ensuring sustainability of improvements. Moreover, integrating AI-driven predictive maintenance strategies could further optimize operational efficiency by anticipating equipment failures and scheduling interventions proactively, significantly reducing unplanned downtime and associated costs [83]. This commitment to ongoing evaluation and adaptation ensures that the urban rail system remains responsive to evolving passenger demands and technological advancements, fostering a resilient and high-performing transportation network. This iterative optimization, underpinned by intelligent systems, ensures that the service design remains agile and capable of adapting to unforeseen challenges and opportunities within the urban mobility landscape [84].

Policy implications extend beyond individual stations. Lessons learned from Jatimulya can be scaled to other stations and eventually to other transport modes. Standardizing best practices in signage hierarchy, accessibility benchmarks, and disruption communication protocols will create consistency across the network. This systemic approach, informed by data-driven insights, ensures that infrastructural investments and management strategies yield optimal benefits for sustainable urban development and an enhanced quality of life [85]. A strong transport authority and integrated master plan, coupled with sustainable funding, are crucial for achieving a robust and sustainable urban transportation system [86]. This requires significant investment in infrastructure and technology, demanding a clear understanding of urban planning and passenger needs [87].

Furthermore, collaboration between operators, regulators, and technology providers is essential. Policies that encourage digital innovation, accessibility compliance, and customer-centric design will provide the regulatory foundation for service transformation. This collaborative ecosystem facilitates the rapid deployment of smart technologies and fosters an environment conducive to ongoing research and development in urban mobility solutions [88]. Ultimately, a holistic approach combining AI-enhanced service design with robust policy frameworks can elevate urban rail systems into highly efficient, resilient, and passenger-centric transportation

DOI: https://doi.org/ 10.31004/riggs.v4i3.2386

networks, significantly contributing to the livability and economic vitality of metropolitan areas (Xuto et al., 2021). This integrated approach contributes to a sustainable transportation ecosystem by optimizing resource utilization and minimizing environmental impact [89][90]. The overarching goal is to transform urban rail into a seamless, interconnected component of a smart city infrastructure, thereby enhancing overall urban mobility and quality of life.

In conclusion, continuous improvement grounded in AI-enhanced service design has the potential to elevate Jabodebek LRT as a benchmark for smart rail systems in Indonesia. It demonstrates how operational efficiency, passenger satisfaction, and policy goals can converge in a unified strategy for sustainable mobility. This integrated approach fosters a smarter transport system that caters to social, economic, and environmental sustainability, laying the groundwork for more livable urban futures [91]. This paradigm shift necessitates a re-evaluation of traditional urban planning methodologies, emphasizing dynamic, data-driven frameworks that can adapt to evolving societal needs and technological advancements [92]. This holistic perspective ensures that urban rail infrastructure and services are not only efficient but also resilient and adaptable to future challenges, such as climate change and evolving demographic patterns [93].

4. Conclusion

This study concludes that the successful implementation of urban rail services such as the Jabodebek LRT requires more than physical infrastructure; it demands an intelligent and adaptive service design that integrates artificial intelligence into established frameworks of service blueprint, servicescape, and service encounters. At Jatimulya Station, persistent issues such as ticketing inefficiencies, overcrowding, accessibility challenges, and inconsistent passenger information highlight the limitations of conventional operational approaches. By embedding AI into service blueprinting, operators can shift from static, descriptive models to dynamic, predictive, and prescriptive systems capable of optimizing passenger flows, staff deployment, and real-time disruption management. Similarly, digital servicescape innovations enhance inclusivity, wayfinding, and user trust by synchronizing physical and digital touchpoints, while AI-supported service encounters strengthen the synergy between human interactions and machine-driven insights. Collectively, these findings demonstrate that AI-enhanced service design not only improves operational efficiency and passenger satisfaction but also contributes strategically to broader policy goals of sustainable mobility, equity, and trust in public transportation. Therefore, the Jabodebek LRT, through continuous improvement and integration of AI-enabled frameworks, has the potential to evolve into a benchmark for smart urban rail services in Southeast Asia, reinforcing Indonesia's position in advancing future-ready, sustainable, and people-centered mobility systems.

Acknowledgment

The researcher wishes to extend profound appreciation to Universitas Ary Ginanjar for its generous financial support and institutional assistance throughout the course of this research. The provision of material resources, academic guidance, and an enabling environment for scholarly work has played a pivotal role in ensuring the successful completion of this study. Such support not only facilitated the smooth execution of the research process but also reflected the University's unwavering commitment to advancing knowledge, fostering innovation, and encouraging the academic growth of its researchers. The researcher is particularly grateful for the University's recognition of the importance of this study, which seeks to contribute to contemporary debates on artificial intelligence and communication strategies. Without the invaluable support and encouragement from Universitas Ary Ginanjar, this work would not have been possible. The researcher sincerely acknowledges this contribution as a significant factor in the realization of the objectives and outcomes of this research.

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