Int. J. Production Economics 274 (2024) 109324

Contents lists available at ScienceDirect

International Journal of Production Economics

journal homepage: www.elsevier.com/locate/ijpe

Artificial intelligence and policy making; can small municipalities enable digital transformation?

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ARTICLE INFO

Keywords:
Digital transformation
Strategic decision making
Policy
Generative AI
SEM

ABSTRACT

This study investigates digital transformation and the usability of emerging technologies in policymaking. Prior studies categorised digital transformation into three distinct phases of digitisation, digitalisation, and digital transformation. They mainly focus on the operational or functional levels, however, this study considers digital transformation at the strategic level. Previous studies confirmed that using new emerging AI-based technologies will enable organisations to use digital transformation to achieve higher efficiency. A novel methodological AI-based approach for policymaking was constructed into three phases through the lens of organisational learning theory. The proposed framework was validated using a case study in the transportation industry of a small municipality. In the selected case study, a confirmatory model was developed and tested utilising the Structural Equation Modelling with data collected from a survey of 494 local stakeholders. Artificial Neural Network was utilised to predict and then to identify the most appropriate policy according to cost, feasibility, and impact criteria amongst six policies extracted from the literature. The results from this research confirm that utilisation of the AI-based strategic decision-making through the proposed generative AI platform at strategic level outperforms human decision-making in terms of applicability, efficiency, and accuracy.

1. Introduction

In recent years, the phenomenon of digital transformation has emerged as a fundamental force reshaping businesses and industries (Kraus et al., 2021a,b). It unfolds through three distinctive phases ranging from relatively simple to more pervasive changes of digital change (Verhoef et al., 2021). Each phase not only alters business operations but also gives rise to innovative business models. The first phase of digital transformation, digitisation, revolves around the digitisation of existing processes and operations, signifying the initial step where analogue systems and manual processes transition into digital formats such that computers can store process, and transmit such information (Bloomberg, 2018; Mugge et al., 2020; Verhoef et al., 2021). In transportation, this phase has witnessed the introduction of technologies like electronic ticketing (Genzorova et al., 2019), GPS navigation (Nykyforuk et al., 2019), and online booking systems (Campos, 2018) making travel more convenient and efficient.

The second phase, digitalisation, describes how information technology or digital technologies can be used to alter existing business processes and operations (Bloomberg, 2018; Ivančić et al., 2019; Verhoef et al., 2021). It has been well known that unemployment reduction, quality of life improvement, and boosting citizen access to public services are all influenced by digitalisation (Parviainen et al., 2017). For example, during this phase real-time data sharing takes centre stage, fostering increased communication between vehicles, infrastructure, and passengers. Concepts such as smart traffic management systems (Lorenz et al., 2022) and Internet of Things (IoT)-enabled vehicles gain importance (Mohammadi and Rashidzadeh, 2021). These IoT devices generate a wealth of data, ranging from traffic patterns to vehicle diagnostics, significantly influencing the decision-making processes of both commuters and transportation providers (Tyagi et al., 2019).

However, it is the third and most transformative phase, known as digital transformation (DT) or the "pervasive" phase (Verhoef et al., 2021). In this phase, digital technologies, including IoT, give birth to entirely novel business models that disrupt traditional paradigms (Vaska et al., 2021). DT introduces a new business model by implementing a new business logic to create and capture value (e.g., Baiyere et al., 2020). Moreover, it marks a phase where data-driven decision-making

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https://doi.org/10.1016/j.ijpe.2024.109324
Received 10 November 2023; Received in revised form 31 May 2024; Accepted 22 June 2024
Available online 25 June 2024

becomes a cornerstone of effective transportation management (Wu et al., 2021).

DT tends to minimise human interactions by making informed decisions. Decision-making is a fundamental cognitive process that humans engage in a daily basis. It involves selecting a course of action from various available alternatives, with the aim of achieving a specific goal or outcome (Edwards, 1954). It can be a complex and multidimensional process influenced by a variety of factors, including personal values, preferences, information, and external circumstances. However, effective decision-making in business contexts requires a deep understanding of technology, a focus on human and machine collaboration, and a commitment to ethical and sustainable practices (Xu et al., 2021). A decision support system (DSS) usually helps a decision maker to make efficient and more reliable decisions (Bonczek et al., 2014). DT has a profound influence on decision-making processes in various domains, including business (Schwertner, 2017), healthcare (Kraus et al., 2021a, b), education (Benavides et al., 2020), transportation (Naumova et al., 2020), and more. It fundamentally alters how decisions are made, offering new opportunities, challenges, and capabilities.

Looking ahead, the evolution of DT toward industry 4.0 offers a fruitful integration (De Bem Machado et al., 2022). Industry 4.0, also known as the fourth industrial revolution, has a profound influence on the transportation industry. It introduces a range of technologies and concepts that revolutionize how transportation systems are designed, operated, and maintained. Overall, Industry 4.0 is reshaping the transportation industry by making it more efficient, safer, and passenger friendly (Bousdekis et al., 2021). Industry 4.0 and the emerging concept of Industry 5.0 are transformative paradigms in manufacturing and industry that significantly influence decision-making processes (Nayeri et al., 2023). The evolution from Industry 4.0 to Industry 5.0 introduces new layers of complexity. This emerging era seeks to revolutionize various industries, including transportation, by integrating advanced technologies like Artificial Intelligence (AI), robotics, and IoT into decision-making processes. Industry 5.0 aims to enhance decision-making by harnessing the power of data analytics and automation, offering unprecedented insights and efficiency across industries (Nayeri et al., 2023). Research into how Industry 5.0 can further extend the impact of DT (Kraus et al., 2023) in transportation and how it influences customer behavioural decisions. In both Industry 4.0 and Industry 5.0, data-driven decision-making is essential. The distinction lies in Industry 5.0's emphasis on the integration of human judgment and machine capabilities. It requires a shift from purely data-driven decisions to a more holistic approach that values human expertise, creativity, and ethical considerations alongside technological advancements such as generative AI.

Generative AI is a type of artificial intelligence algorithm that have gained significant attention for its ability to generate data, images, and content that closely resembles real, human-created content (Cao et al., 2023; Porsdam Mann et al., 2023). For example, Generative Pre-trained Transformer (GPT) is used to imitate human writing efficiently by using models that utilises big data such as ChatGPT (Baidoo-Anu and Ansah, 2023). Generative AI and decision-making are closely related, as generative AI can significantly impact the decision-making process in various domains (Chuma and de Oliveira, 2023). Whilst generative AI can offer valuable support and insights for decision-making, it is important to note that the quality and reliability of generative models can vary (Korzynski et al., 2023). Ultimately, the relationship between generative AI and decision-making depends on the specific application and the goals of the decision-maker. Furthermore, this integration emerged as a powerful tool that holds great potential to support policymakers and researchers in various aspects of policy development and decision-making (Mittelsteadt, 2023). It holds immense promise in enhancing the policy development process and supporting data-driven, evidence-based decision-making. As the technology continues to evolve, policymakers must engage in ongoing dialogue and collaboration with AI experts, researchers, and the public to ensure its responsible and effective use in shaping the policies of the future. These days machine learning (ML) and artificial neural networks (ANN) are utilised in the DSS to improve the quality and precision of the prediction for better decisions. The impact of ANN-based DSS has been observed and analysed by Fonseca and Navaresse (2002) in the job-shop simulation. The quality of decision making in a DSS depends on two factors 1) the quality of prediction and 2) the extracted possible solutions. ML can provide a good solution for both factors to ensure that not only the quality of prediction is good enough but also the possible solutions can be determined properly. Mumali (2022) reviewed the studies on ANN-based DSS in manufacturing processes. Also, Alvarez et al. (2021) explored that in the non-classical decision-making approaches, hybrid methods with an ML algorithm may lead to overcoming the current limitations of the multiple criteria decision-making.

Despite many prior studies focused on the impact of DT on business performance (Mubarak et al., 2019; Popović et al., 2019; Zhai et al., 2022), little was researched on the impact of generative AI on policymaking (Craglia, 2020; Kitsios and Kamariotou, 2021). This research considers the presence of big data and the emerging digital technologies such as artificial intelligence that play a big role in shaping the decision makings in the transportation industry. It will provide an understanding of how important this new technology can provide clear signals to policy makers to make suitable policies. This study focuses on the third phase, digital transformation, of which introduces new models based on the digital resource of big data analytics capability. To the best of our knowledge, no prior studies provided an artificial intelligent-based framework for embedding the digital transformation of organisations in a strategic level of decision-making. Thus, the research question is:

RQ: To what extent can digital transformation be embedded into the policymaking?

This paper develops a conceptual framework for digital transformation at the strategic level. A three-phase model is developed to achieve artificial intelligence-based policy making. The proposed methodology is validated through a case study of mobility choice in a municipality in Greece. The case study explores how passengers make their mobility choices based on multiple factors such as quality and service. The ultimate aim of this paper is to determine the optimal policy.

The remainder of the paper is structured as follows: A revision of prior studies including digital transformation and its levels, generative AI for digital transformation, related theories, and research gap are discussed in the literature review section. Research methodology section discusses the digital transformation using the proposed AI-based strategic decision-making framework and the case study used to validate the framework. Following, the proposed framework is validated with the reported results. Finally, the last section discusses the implications of the research including theoretical, methodological, and empirical. This concludes the paper and provides recommendations for future research.

2. Literature review

Although there are several phases of DT's maturity in an organisation, it is a complex process that includes the integration of digital technologies (Hermann et al., 2024) into several business processes (Amankwaa et al., 2024; Ooi et al., 2023). Prior studies have considered whether and how to accelerate DT drawn upon knowledge provided by data-driven insight (Zhu and Li, 2023). This indicates that decision making is also influenced by DT. In the management literature it has been identified that decision making is differentiated at various organisational levels. According to Heyder et al. (2023) these levels are described as Operational, Functional/Tactical, and Strategic level. At the operational level, it has been found that DT promotes the utilisation of digital technologies into existing processes to enhance efficiency and streamline day-to-day operations (Amankwaa et al., 2024; Fang and Ju, 2024). DT at operational level focuses on the daily activities and short-term decisions mostly by low-level managers. This means that actions on the functional level is to optimise operations by meeting the budget targets and being productive operatively. Decisions on this basis is directly linked to the daily working routines to achieve functional strategies. In overall, decisions made at the operational level do contribute to making appropriate decisions at the functional level.

According to Heyder et al. (2023) functional level decisions are based on middle planning horizons. This entails the coordination and control activities. A study by Bansal et al. (2023) suggested that DT is the successful integration of digital infrastructure, digital architecture, and individual capability and creativity. Similarly, Matarazzo et al. (2021) indicated that those capabilities integrate digital knowledge throughout at cross-functional teams. This is usually linked to the controlling and coordination of digital technologies by middle managers such as organisational department managers (Heyder et al., 2023). The final and for most important organisational level is decisions made at the strategic level. This is based on long-term planning horizons. At this level, actions mainly on the business level to achieve the several business strategies by executives and senior management involvement (Keding and Meissner, 2021). Amankwaa et al. (2024) stated that DT at this level refers to how digital technologies are incorporated across business processes, high level operational priorities and long-term planning for decision making. At this level, organisations led by senior management strive to be adaptable to the rapidly evolving technological advancement in the market (Dubey et al., 2024).

It has been evidently clear in the literature that the linkage between DT and decision making is impactful at different organisational levels. This encompasses the utilisation of various digital technologies including Generative AI implemented using diversified strategies to accommodate the technological advancement in the competitive environment. Previous studies have focused on AI and generative AI as an effective tool to improve efficiency of companies which leads to a DT (Holmström and Carroll, 2024), however they express that it has been poorly studied (Kohli and Melville, 2019). Generative AI has the potential to generate artificial data (Baidoo-Anu and Ansah, 2023) and simulate scenarios (Coletta et al., 2021) at different organisational levels. For instance, at the functional level and within the marketing industry (Sinha et al., 2023) noted that generative AI facilitates creating novel advertisement formats that support the coordination with other organisational departments. Within the healthcare industry and at the operational level it can offer linguistic support between doctors and patients (Ooi et al., 2023). This opens new opportunities for policy-makers seeking data-driven insights and innovative solutions (Dwivedi et al., 2023; Porsdam Mannet al., 2023). Generative AI has emerged in the past few years as a powerful and transformative tool reshaping the landscape of policymaking (Dwivedi et al., 2023). However, the true promise of generative AI lies not merely in its autonomous capabilities but in its capacity to collaborate with human decision-makers (Fui-Hoon Nah et al., 2023), enhancing the policymaking process and fostering evidence-based decisions.

This sort of collaboration between executives' rich experience and generative AI contributes hugely towards organisational strategic decisions. A new creativity that benefits both industry and consumers is due to the evolved relationship (Jiang et al., 2022; Turban et al., 2018). Amankwaa et al. (2024) noted that policymakers are offered with supportive strategic insights via the utilisation of generative AI. Although it has been claimed previously that generative AI can be used as a tool to facilitate knowledge within the educational industry (Lim et al., 2023), this exemplifies the organisational need to advance and succeed in the industry through obtaining knowledge. There are also some strategic issues in utilising the generative AI such as ethical considerations. Yet, Dalalah and Dalalah (2023) indicated that further research is needed to determine the impact of generative AI on knowledge acquisition and DT.

Utilised tools for DT create and facilitate a learning environment for the organisation to obtain knowledge. This sort of knowledge obtained is translated in terms of applicability within relevant industries mostly at mid and low levels (Ooi et al., 2023). With that, generative AI still poses some concerns to the quality of its output and knowledge contribution to the management literature (Lee and Tseng, 2024) and particularly to the strategic level of the organisation.

The concept of obtaining knowledge through learning through the utilisation of DT is theorised in multiple disciplines. This research identified five relevant theories and explains the process of selecting the most appropriate underpinning theory for this research. To begin with the most popular theory based on the number of published studies, resource-based view (RBV) highlights the importance of organisational culture and resource complementarity in achieving a competitive advantage (Guo, X. et al., 2023; Haftor and Climent, 2021; Oludapo et al., 2024; Li, 2022; Zhu and Li, 2023). In brief, RBV emphasizes the role of unique resources and capabilities. Digital technologies including digital analytics and platforms are used to exploit organisational resources shaping their DT and improving their organisational performance (Belhadi et al., 2024; Huang et al., 2023; Meena et al., 2023).

Meanwhile, Dynamic Capability theory is enabler of change allowing management to adapt, innovate, and reconfigure capabilities in response to changing environments such as technological turbulences (Papanagnou et al., 2022; Qin et al., 2021; Wang et al., 2023; Ye et al., 2022). This theory suggests that organisations must have the ability to adapt, learn, and exploit opportunities through coopetition, to improve business performance using digital technologies (Javeed and Akram, 2024; Li, 2022; Zhao et al., 2023).

Institutional theory represents regulatory, normative, and cognitive influences encourage organisations to respond and adopt specific learning behaviours (AlNuaimi et al., 2022; Li, 2022; Marino-Romero et al., 2024; Tiwari et al., 2024). This theory describes DT as a tool for transforming business processes, cultures, and organisational aspects to meet changing market requirements brought about by digital technologies through the notion of understanding and learning (Gu et al., 2023; Kassem and Ahmed, 2022; Simmonds et al., 2021).

Additionally, Organisational Information Processing Theory emphasizes the importance how organisations should manage information and the processing of information to achieve and gain competitive advantage (Belhadi et al., 2024; Enrique et al., 2022).

Last but not least, Organisational Learning Theory (OLT) suggests that organisations that actively acquire, share, and apply knowledge through coopetitive relationships are better equipped to innovate and adapt to changing market dynamics, resulting in enhanced performance (Centobelli et al., 2020; Lin and Lin, 2023; Liu et al., 2024; Meena et al., 2023). Within the context of DT, it emphasizes the significance of continuous learning and knowledge sharing within an organisation (Agnihotri et al., 2023; Zhang et al., 2021). This implies that decisions are based on knowledge to ultimately enhance organisational performance. The comparison amongst the five aforementioned theories are summarized in Table 1.

OLT has been described as the practical knowledge that attempts to optimise the creation and behaviour of organisations and to understand how different circumstances influences organisations to make decisions (Feng et al., 2022). As this research's aim is investigating how organisations can utilise DT at the strategic level in an attempt to learn and develop knowledge to make informed decisions, OLT fits well with the study's aim.

Collectively, this research investigates how generative AI as a DT tool would support decision-making at the top organisational level known as the strategic level. It is anticipated that the generative AI through knowledge learning would produce valuable insights equivalent to those with rich experience such as executives and senior management. Hence, organisations would be able to make informed decisions on the basis of data. This conceptualisation is supported by the underpinning theory of Organisational Learning Theory.

Table 1
Summarized relevant digital transformation theories.

Theory	Nature of Decision	Focus	Role of technology	Suitability to the study (Role of DT)	Weaknesses to the study	References
Organisational Learning Theory (OLT)	Decisions based on Knowledge.	To acquire, create, and utilise knowledge to enhance performance.	Technology plays a crucial role in knowledge acquisition and dissemination. Adapts new technological tools and integrate them into their processes.	DT coopetitve influences knowledge, shared resources, and capabilities with their competitors. Also, it focuses at the strategic level.	It does not cover operational perspectives.	Agnihotri et al. (2023); Centobelli et al. (2020); Lin and Lin (2023); Liu et al. (2024); Meena et al. (2023); Zhang et al. (2021)
Dynamic Capability (DC)	Decisions based on sensing.	To adapt, innovate, and reconfigure resources and capabilities in response to changing environments.	Technology utilised to create, modify, and recombine resources dynamically.	DT utilised to change organisation's structure and boundaries. Also, it allows companies to discover opportunities through the use of technology.	Can be substitutable and underlying operational processes.	Javeed and Akram (2024); Li (2022); Papanagnou et al. (2022); Qin et al. (2021); Wang et al. (2023); Ye et al. (2022); Zhao et al. (2023)
Resource-based View (RBV)	Decisions based on resources.	Exploit unique resources and capabilities contributing to competitive advantage.	Technology can be a critical resource- to sustain competitive advantage.	DT leverages various technological advancements such as data analytics and digital platforms identifying and capitalizing resources complementarities. It posits that firm's resources can provide enhanced performance.	Focuses on the firm level.	Guo et al. (2023); Haftor and Climent (2021); Huang et al. (2023); Oludapo et al. (2024); Zhu and Li (2023)
Institutional Theory (IT)	Decisions based on norms.	Conform to societal norms, rules, and expectations.	Technology adoption because of institutional pressures.	DT transforms firm's cultures, processes, and organisational aspects to address the requirements of the changing market. Reconceptualising features of organisational environments.	Lack of consideration of technological advancement.	AlNuaimi et al. (2022); Gu et al. (2023); Kassem and Ahmed (2022); Marino-Romero et al. (2024); Simmonds et al. (2021); Tiwari et al. (2024)
Organisational Information Processing Theory (OIPT)	Decisions based on information-processing.	To collect, analyse, and use information effectively.	Information processing through the utilisation of digital tools.	DT facilitates the capabilities to improve information processing. It handles dynamic organisational processes of learning.	Focuses on organisational innovation via processing information.	Belhadi et al. (2024); Enrique et al. (2022); Hamann-Lohmer et al. (2023); Xie et al. (2022)

3. Research methodology

3.1. Proposed artificial intelligence-based strategic decision-making framework

In this study, a systematic three-phase decision-making process is utilised to determine the most effective policy from the potential policies. The proposed framework on digital transformation at the strategic level contains three main phases. In the first phase, structural equation modelling (SEM) is used to test the hypotheses considering multiple tests. The results will confirm the significance of the relationships between factors on the targeted dependent variable. In addition, the confirmed factors are extracted for the use of ANN analysis. A predictive tool based on the ANN is created in the second phase. This tool can be used for making a decision and selecting a proper transportation policy. To make an informed decision, three factors were considered in this research which are cost implementation (CM), feasibility implementation (FM) and impact of policy on dependent variable (IM). In the third

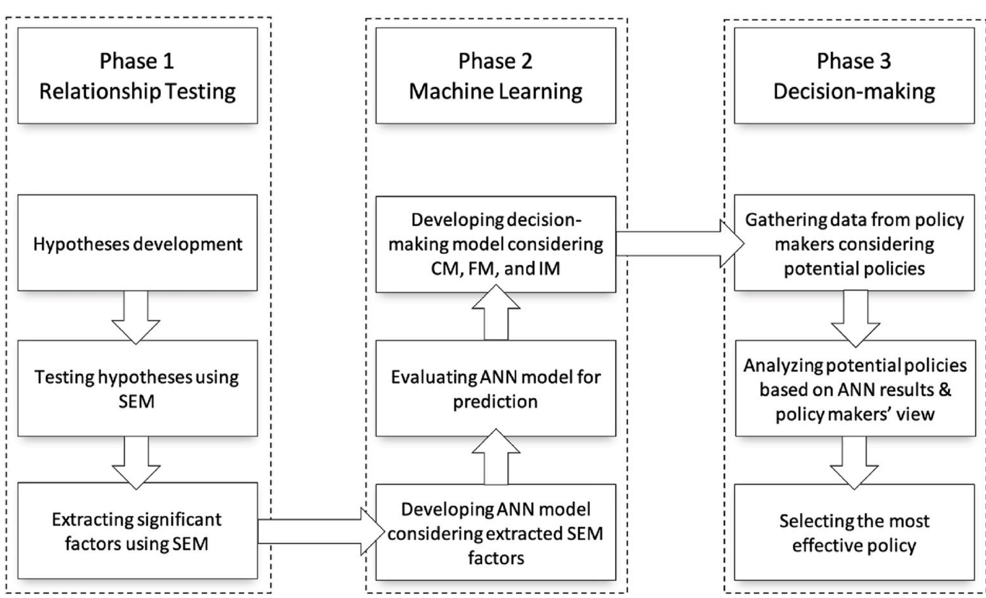

Fig. 1. Proposed methodology for AI-based policy making for strategic digital transformation.

phase, the values of IM for each policy are predicted by using the trained ANN. Then the results are aggregated in an integrated measure to extract the most effective policy. The whole proposed decision-making framework as a part of digital transformation is depicted in Fig. 1. The proposed methodology is discussed with more details in a selected case study which is explained in the next sub-section.

3.2. Case study – transportation policy in AAK municipality in Greece

In the present research the first and second phases uses full dataset collected from transportation passengers in the Agii Anargiri-Kamatero (AAK) municipality. For participants to take part in the survey, the participant should be living in the municipality and either working within the limits or within the metropolitan agglomeration area of Athens. As part of the EU funded project CITYMOBILNET, the municipality developed and distributed with the support of the Transport Systems Laboratory of the University of Piraeus a travel survey. The collected data were intended to be used for the development of sustainable transportation policies as well as integrated traffic planning in the city. The survey was distributed through specific access channels like elementary schools, Elderly Open Care Centres, and municipal agencies to residents of the municipality of AAK as well as residents of neighbouring municipalities, who have specific mobility interests in the municipality. This resulted in a significant return of the surveys; out of the 1200 questionnaires sent 672 were returned accommodating 56% response rate. Of those, 95 were only partially completed, of which 577 were deemed useable.

In the third phase a follow-up questionnaire was designed on the basis of extracting potential policies from the literature for confirming ML results. Seven transportation policy and decision-makers from the municipality of AAK were invited to complete the survey. The questionnaire contains three measurable items using Likert 5-point scale. These items are CM, FM, and IM on mobility choice (MC) for all potential policies. Out of seven participants only five took part in the follow-up questionnaire.

3.2.1. Digital transformation tool utilisation related to the case study

Transportation policies have been widely studied resulting in an improved transportation costs of which enhances economic growth and development (Berg et al., 2015). Those policies originate from infrastructure to vehicle dependency (MacKett, 2002). In most cases, measures are developed to minimise number of private vehicle (PV) owners that in turn reduces crowded traffic through suggesting alternative transportation. These include, but not limited to, the use of public transport (PT) (Yen et al., 2017), transportation facilitating for social inclusion (Lucas, 2006), and active transportation such as cycling or walking (CW) (Farinloye et al., 2019).

A number of different tools have been used to identify the factors. Eboli and Mazzulla (2008) and Hensher and Greene (2003) adopted Multinomial Logit model (MNL). More importantly, it is noted that SEM is adopted in service quality and transportation literature as a tool for policymakers to improve decision-making (De Oña et al., 2013; De Oña, 2020; Deb and Ahmed, 2018; Rosell and Allen, 2020; Zhang et al., 2019). The technique tests various relationships amongst observed and unobserved variables (Golob, 2003). However, generative AI stands at the intersection of ML and SEM (Al-Khatib, 2023), offering a unique and innovative approach to understanding and addressing complex policy challenges. ML, with its ability to analyse vast datasets and derive patterns and insights, is instrumental in generating synthetic data and predicting outcomes (DeGregory et al., 2018). SEM, on the other hand, provides a rigorous framework to model and test relationships between variables, making it a valuable tool for evaluating policy impact and effectiveness (Hair et al., 2021).

Decision-making on the transportation literature is not limited to SEM, prior studies used ML as an informative analysis and decision-making in transportation studies. The analysis shows that some of studies only considered the ML algorithms for prediction. However, there are some studies which used both ML and optimisation. The comparison of previous studies reported in Table 2 shows that the current study is the only one which has used the SEM, ANN, and decision-making to choose the effective transportation policy. Determination of main effective factors is one of the important steps of building predictive models. Usual classic statistical methods are used to extract those factors. Then a predictive model can perform more effectively for better prediction. In the previous studies SEM has been used to configure the main factors and it has not been used as an initial method to construct the model elements to be used for the effective prediction by ANN. This study utilises the benefits of SEM to extract the main effective factors, and then uses selective factors according to the results of SEM in the prediction stage adopted by ANN. There is a contribution in the combined method which has been used in this study and will lead to effective decision-making.

3.2.2. Phase 1 (hypotheses development)

To propose our hypotheses for extracting those factors, this study considers multiple factors that have either a direct or indirect effect on the MC. These include investigating factors such as social influence, quality of transportation, transportation problems, and travel conditions. Those relationships are illustrated on the conceptualised model in Fig. 2. We elucidate the hypotheses from the following perspectives.

SEM model is usually adopted as a fundamental and powerful technique to explore the interrelationships between distinct factors (Chou and Kim, 2009). De Oña et al. (2013) estimated PT passenger satisfaction, with latent variables the personnel, PT comfort, and service

Table 2
Review of Existing Research using SEM and/or ANN in transportation industry.

Reference	Method	Area of study	Results
Budak and Sarvari (2021)	An integrated ML-based methodology	Sustainable road freight transportation	The proposed method performs better than classic methods.
Abdirassilov and Sładkowski (2018)	ANN	Container train flows	Achieved prediction by the ANN is confirmed.
Alsrehin et al. (2019)	Data Mining and ML	Intelligent Transportation and Control Systems	There is no standard traffic management approach
Beşikçi et al. (2016)	ANN based DSS	Energy efficient ship operations	The superiority of ANN was confirmed. A DSS was developed with two scenarios.
Amiri et al. (2020)	Decision trees, random forest, and neural networks	Predicting household transportation energy consumption	ML algorithms have significantly higher accuracy
Mahpour and El-Diraby (2022)	ML and Markov Chain for prediction and TOPSIS for decision Making	Road Maintenance Policy-Making	The optimal policy was selected
Sun and Wandelt (2021)	ML techniques	Transportation mode choice behaviour	Passengers preferably select the first-ranked alternative provided by the route recommendation system
Ton et al. (2019)	Mixed multinomial logit	Cycling and walking mode choice in Netherland	Active mode is very sensitive to changes of the trip characteristics and the environment
This research	SEM, ANN, and decision-making	Transportation policy	The proposed method can determine a preferred transportation policy

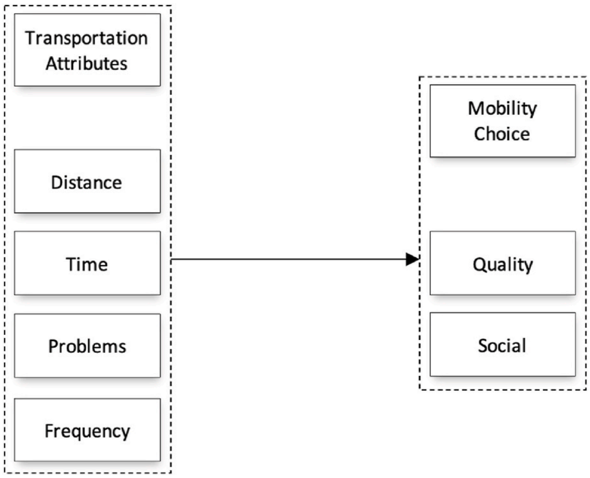

Fig. 2. Phase 1 conceptualised model.

emphasizing that the unobserved characteristics of quality is the most important variable over comfort and personnel based on data retrieved from the Granada Travel Survey. Similarly, in a later study de Oña et al. (2015) used the same method to analyse the relationship between perceived accessibility and customer satisfaction in the Seville (ES) Metro system. Another research by Mandhani et al. (2020) looked into the interrelationships amongst service quality factors of Metro Rail Transit System using SEM approach. The model used facilitates in discovering hidden interrelationships through a systematic manner. The outcome of the interrelationships analysis provides policy and decision-makers the knowledge of formulating effective investment plans and strategies.

These MCs are driven by theoretical background including the Theory of Reasoned Action (TRA) and Theory of Planned Behaviour (TPB) as a process to measure attitude towards MC. On one hand, TRA provides a background of behavioural intention on attitude and behaviour (Ajzen and Fishbein, 1975). On the other hand, TPB offers a connection between principles and behaviour (Ajzen, 1985). TRA and TPB explain that behavioural response is driven by how great the intention or motivation is (Ajzen, 1985; Scott et al., 2016). Transportation quality factors have been associated with the overall satisfaction ranking. Clearly, these factors are affected by the socioeconomic characteristics of the passengers as well as how much dependent they are on PT usage. These quality factors include comfort and hygiene, Wi-Fi service availability, air-conditioning, trip duration, and traffic congestion on PT usage (Chee and Fernandez, 2013; Efthymiou et al., 2014; Ubillos and Sainz, 2004). Simultaneously, it is expected that economic crisis would affect the satisfaction of transportation passengers including PV, PT, and CW (Botzoris, 2020; Efthymiou and Antoniou, 2017; Mitsakis et al., 2013; Moschovou and Tyrinopoulos, 2018). This study will focus on trip frequency, distance, and duration as part of quality of service affecting MC. Thus, this study suggests testing the following hypotheses.

H1. Trip Frequency has a positive influence on trip Time

H2. Trip Time has a positive influence on trip Distance

H3. Trip Distance has a positive influence on transportation Quality

In transportation behaviour a number of studies focused on studying passengers' behaviour according to behaviour and rational principles that determine passenger's MC. One of the most studied factors that impacts on MC is social factor (Axhausen et al., 2003). Although social factor may directly influence the MC, there are still interrelationships that are not discovered in combination to travel conditions and other factors (Phithakkitnukoon et al., 2017). Thus, the influence of other factors could justify how the passenger behaves in choosing appropriate MC. For instance, passengers may change their behaviours aligning their behaviour with close ones such as friends (McPherson et al., 2001). The spatial factor of social networks is limited in the literature theoretically and empirically (Maness et al., 2015). Thus, this study proposes these hypotheses.

H4. Transportation Quality has a positive influence on Mobility Choice based on Social boundaries

H5. Transportation Quality mediates the relationship between travel Distance and on Mobility Choice based Social boundaries

In a similar approach, mobility situations delaying and affecting passengers such as roadwork and accidents are external factors affecting the quality of service influencing MC. There is a limited literature that considers developing models evaluating the impact of transportation problems (Ben-Akiva et al., 1997). Passengers' behaviour towards those problems are measurable by considering the preferences and its repetition as an observable factor. This simplifies analysing the pattern of MC through considering the satisfaction factor (Ben-Akiva et al., 1991; Dia, 2002). Thus, this study proposes the following hypotheses.

H6. Trip Distance has a positive influence on transportation Problems

H7. Transportation Problems has a positive influence on transportation Quality

H8. Transportation Quality mediates the relationship between transportation Problems and Mobility Choice based on Social boundaries

In order to use ML in identifying the most effective policy, a number of policies have to be tested to confirm the results. It is noted that there are some studies that suggest implementing or developing new or existing transportation policies for various regions depending on demands. A number of policies and MC have been reviewed across different regions supplying a range of solutions including urban areas (Fageda et al., 2018; Kirschner and Lanzendorf, 2020). It is noted that it has been challenging for developing countries to implement policies (Berg et al., 2017) regardless of the continuous effort in developing those policies (Omiunu, 1987). Many researchers consider PT as the most important MC. More precisely, most studies focus on analysing the factors influencing the acceptance of PT systems and how behaviour can be shifted from PV usage to either PT or other (more) sustainable MC such as CW. The economic crisis is generally regarded as leading passengers towards non PV usage by many researchers (Le Néchet et al., 2016; Papagiannakis et al., 2018; Ray et al., 2012) since decision-makers, being integral parts of households that undergo personal changes, change lifestyles and economic spending patterns. In order to make this transition, the PT options have to offer improved passenger satisfaction and quality of service.

Proposed transportation policies (PTPs) are reviewed and supported by prior research (see Table 3). These PTPs will be empirically tested to determine how ML can identify similar or even better decisions in comparison with those decisions made by policy and decision-makers.

Establishing more public spaces diversely in the region (PTP1): it is expected that urban areas developed will enhance the transportation system. This transportation policy originates solely on improving economic growth. Developing facilities, services, communal activities for all ages in urban area ensuring new transportation network system is in place integrated with social equity and environmental management.

Increase social awareness, socialising or culturalization (PTP2): passengers in urban areas are encouraged to explore pathways for culturalization as a mean to increase social awareness about existing transportation network systems. This could encourage transportation passengers to reduce the use of PV and switch to PT considering the awareness of social value and its impact on environmental behaviour.

Improving the quality of public transportation facilities (PTP3): continuous improvement of the service quality of PT and facilities are deemed very important. In most cases the aspects of pricing and demand is associated with the quality of transportation facilities evaluating the

Table 3
Proposed transportation polices.

Sources	PTP1	PTP2	PTP3	PTP4	PTP5	PTP6
Wang et al. (2020)	x					
Hu and Yuan (2018)	x					
Huang (2019)	x					
Zhou and Zhang (2021)	x					
Guzman et al. (2020)	x					
Pradhan et al. (2021)	x					
Hopkins (2016)		x				
Mulley et al. (2017)		x				
Chorus and Timmermans (2009)		x				
Hrelja (2015)		x				
Mandhani et al. (2020)			x			
De Oña (2020)			x			
Kim et al. (2020)			x			
Kearns et al. (2019)				x		
Lin et al. (2017)				x		
Tscharaktschiew and Hirte (2012)				x		
Tang et al. (2020)					x	
Nordhoff et al. (2020)					x	
Haque and Haque (2018)					x	
Woods and Masthoff (2017)					x	
Crayton and Meier (2017)						x
Engström et al. (2019)						x

transportation systems. The policy is determined by passengers' satisfaction through a range of quality variation including quality of perceived PT service, quality of expected PT service, quality of planned trip using PT service, etc.

Increasing the number of public transportation facilities/vehicles (PTP4): like quality quantity is also deemed vital where the number of vehicles could be increased to match the demand in the urban area. The proposed policy considers the frequency, transportation conditions, as well as transportation passenger's needs. However, this policy is not limited to vehicles, this includes increasing the number of facilities and transportation network systems such as including walking and cycling routes in more crowded areas.

Improving transportation safety (PTP5): this policy is proposed specifically for those urban areas with limited infrastructure and is under development. It is expected to have measures for improving transportation safety including the area or site, the vehicle, and the factor. Legal measures and requirements could be put in place to ensure transportation passengers are not endangered encouraging people to use active transportation such as CW.

Setting more restrictive regulations on using Private Vehicles (PTP6): the main purpose of proposing this policy is to allow gradual improvement to the sustainability of transportation system. Limiting and restricting the use of PV can be applied at specific locations in crowded urban areas as well as during peak hours. It is observed in large cities that this policy is successfully implemented to control the increase of PV and relieve transportation traffic. However, this policy is rarely observed or implemented in urban areas due to the slight increase of economic growth and population.

To address the first and second phase of this research, the measurable items were extracted from literature to test the interrelationships of the hypothesised factors (see Appendix 1).

4. Analysis and results for the case study

In the selected case study, the results of the survey were analysed using SPSS, SmartPLS, and MatLab utilising full range of statistical methodologies. The dataset was cleaned to ensure that reliability and validity tests of the data was satisfactory. The dataset contained 577 responses, then reduced to 505 due to missing values identified through an unengaged response test which do not attract any major issues (Tabachnick et al., 2007). In overall, the dataset captured 6 variables measured by 25 items.

4.1. Phase 1

In the first stage internal consistency of the variables were tested using Cronbach's alpha (CA) to assess the reliability. This test uses a set of two or more variable indicators. The CA test was satisfied for all variables with values more the threshold of 0.5 as indicated in Appendix 2 (Ramayah, 2011). Next, Composite Reliability (CR) analysis was taken into consideration to assess the variables considering each variable has different loading and this test was satisfied as all variables exhibit loading above the threshold of 0.6 (Hair et al., 2021). Moving forward into testing the variables' convergent validity using the Average Variance Extracted (AVE) of which indicates that all AVE are satisfied having composite reliability is more than 0.6, the convergent validity of the variable can be acceptable (Fornell and Larcker, 1981). Appendix 2 shows the results of the three tests undertaken. Appendix 3 shows the cross loadings for each variable surpassing values less than 0.5.

Once reliability and validity of the variables are confirmed, the path coefficients for each variable were examined. It is suggested to estimate the bootstrap to determine the significance up to 5000 samples (Hair et al., 2021). The proposed hypotheses were examined using the SmartPLS. Fig. 3 shows the results of the path coefficients' and their significance.

Simultaneously, indirect path coefficients (mediation effect) are reported in Appendix 4. The result indicates that there is a full mediation effect. The explanatory power of the conceptualised model was examined using the coefficient of determination (R^2 value) on the dependent variable (Hair et al., 2021). The R^2 value in Social is 0.58 which can be interpreted as 58 per cent of variances that are explained by the variables in this conceptualised model. Table 4 summarises all hypotheses results.

In H1, it was hypothesised that trip Frequency would have a positive direct impact on Time; this was not supported by the data in the model. The impact of trip Time on Distance (H2) was not supported by the model. However, it was observed that the directional connections between Distance and transportation Quality, and Quality's relationship with Social were significant and supported by the data (H3 and H4). H6 and H7 are relationships that examines Distance variable on Problems and Problems on Quality of which both are reported as significant. H5 and H8 relate to the mediation effect of Distance and Problems variables on Social mediated by Quality.

4.2. Phase 2

Considering the validity of framework using the SEM and to validate the conceptualised model, the SEM model was used to predict dependent variables. Prediction errors were calculated considering the actual and predicted values by the SEM model on MC. The parameters/variables used in this analysis are defined as follows.

I	Index for transportation policy (i = 1, …, I)
J	Index for the measure in each strategy (j = 1 CM, j = 2 FM, j = 3 IM)
K	Index for the decision-makers (k = 1, …, K)
CM_{ik}	CM score of policy i defined by decision-maker k
FM_{ik}	FM score of policy i defined by decision-maker k
IM_i^{ANN}	IM score of policy i determined by the ANN
IM_{ik}	IM score of policy i defined by kth decision-maker
$Std_{i,j}$	Standard deviation of scores amongst decision-makers for jth measure on ith policy
AS_i	Total aggregated robust score for policy i with utilisation of ANN
S_i	Aggregated robust score for policy i defined by decision-makers
PS_i^k	Policy score for the ith policy defined by kth decision-maker through a survey

Two calculation methods are designed to aggregate the score for the polices. The first method, all values provided by decision-makers are used to aggregate the results providing the impact value. The second

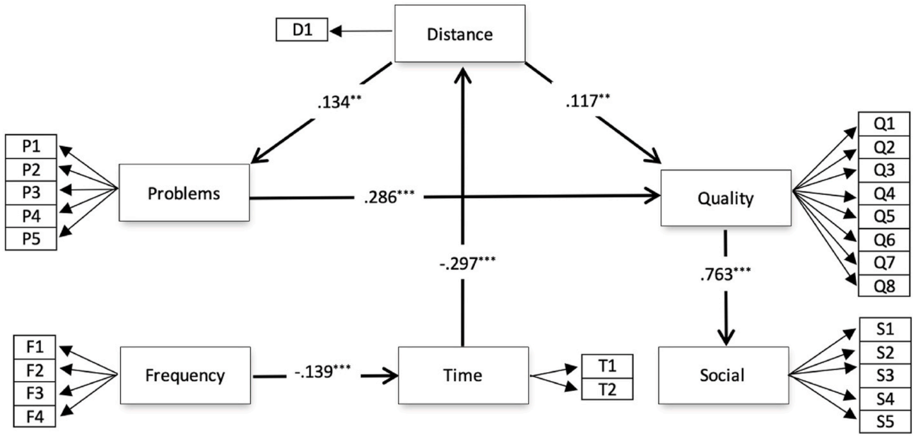

Fig. 3. Sem results.

Table 4
Hypotheses results.

Hypothesis	P-Value	Supported?
H1: Trip Frequency has a positive influence on trip Time	Sig at 0.005	No
H2: Trip Time has a positive influence on trip Distance	Sig at 0.005	No
H3: Trip Distance has a positive influence on transportation Quality	Sig at 0.005	Yes
H4: Transportation Quality has a positive influence on Mobility Choice based on Social boundaries	Sig at 0.005	Yes
H5: Transportation Quality mediates the relationship between travel Distance and on Mobility Choice based Social boundaries	Sig at 0.005	Yes
H6: Trip Distance has a positive influence on transportation Problems	Sig at 0.05	Yes
H7: Transportation Problems has a positive influence on transportation Quality	Sig at 0.005	Yes
H8: Transportation Quality mediates the relationship between transportation Problems and Mobility Choice based on Social boundaries	Sig at 0.005	Yes

method, ANN was used to predict the value of the impact whilst other two measures are calculated according to the survey-data gathered from the policy and decision-makers in AAK municipality. Then, the results of the two methods are compared to see the applicability of the ANN. Finally, the provided aggregated robust scores are compared with the defined policy score and the values provided by policy and decision-makers in the survey (S_i).

$$AS_i = \sqrt[K]{\prod_{k=1}^{K} CM_{ik}} * \sqrt[K]{\prod_{k=1}^{K} FM_{ik}} * IM_i^{ANN} \Bigg/ \left(1 + \sum_{j=1}^{2} Std_{i,j} \Big/ 2\right) \tag{1}$$

$$S_i = \sqrt[K]{\prod_{k=1}^{K} CM_{ik}} * \sqrt[K]{\prod_{k=1}^{K} FM_{ik}} * \sqrt[K]{\prod_{k=1}^{K} IM_{ik}} \Bigg/ \left(1 + \sum_{j=1}^{3} Std_{i,j} \Big/ 3\right) \tag{2}$$

The aggregated robust scores (AS_i, S_i) are calculated according to equations (1) and (2), respectively to compare the results.

Three analytical approaches are considered in this study for comparison and analysis using the three main criteria: CM, FM and IM. The analytical approaches to calculate the aggregated scores for policies are mentioned in Table 5.

The collected data (as scores) of the follow-up survey from the policy and decision-makers of the AAK municipality is reported in Appendix 5. Additionally, Appendix 6 shows how the policy and decision-makers determine the impact of various transportation policies on the confirmed factors. The values have been aggregated according to the provided values by each policy and decision-maker. These values will be considered as input data for the trained ANN to predict the MC. By employing the Multi-Layer Perceptron Neural Network, the MC was predicted for PTP. The results are reported in Table 6.

After the prediction of the MC, two other factors will be aggregated for making a decision to select the most effective PTP.

Table 5
Analytical approaches.

Analytical Approaches	CM	FM	IM
Using the aggregated proposed method (AA1)	Survey	Survey	ANN
Using the provided data by policy and decision-makers (AA2)	Survey	Survey	Survey
Using part of the gathered data (AA3)	–	–	Survey

4.3. Phase 3

According to equations (1) and (2), the measures were calculated which are reported in Table 7. The results confirm that the aggregation score calculated by using the ANN is aligned with the result of the following-up survey as both methods recognise that PTP2, PTP5 and PTP1 are the best policies respectively. It also shows that the proposed method based on the ANN can be used for transportation policy selection and decision-making. According to the provided scores by policy and decision-makers for each policy, it is interesting that although the best policy is still the second policy (as reported in Table 7), but it shows that policy and decision-makers are not precise in aggregation of the measures.

Table 6
MC prediction results using ANN.

Transportation mode choice	Private Vehicle (PV)	Public Transport (PT), Cycling and Walking (CW)	% PT and CW
Current situation using ANN	112	393	28.5%
Predicted values for PTP1	122	383	31.9%
Predicted values for PTP2	128	377	34.0%
Predicted values for PTP3	125	380	32.9%
Predicted values for PTP4	102	403	25.3%
Predicted values for PTP5	134	371	36.1%
Predicted values for PTP6	135	370	36.5%

Table 7
Calculated results for the follow-up survey.

Policies	PTP1	PTP2	PTP 3	PTP 4	PTP 5	PTP 6
Geometric mean for the Impact ($\sqrt[K]{\prod_{K=1}^{K} IM_{ik}}$)	4.4	3.4	5.0	5.0	4.6	4.8
Geometric mean for the Cost ($\sqrt[K]{\prod_{K=1}^{K} CM_{ik}}$)	2	3	1	1	2	2.2
Geometric mean for the feasibility ($\sqrt[K]{\prod_{K=1}^{K} FM_{ik}}$)	1	3.1	1	1	2	1
Geometric mean of the Score for AA3 ($\sqrt[K]{\prod_{K=1}^{K} PS_i^k}$)	5.0	5.8	2.2	1.8	1.6	4.2
Average Standard deviation for the AA1 $\left(1 + \sum_{j=1}^{2} Std_{i,j} /2\right)$	1	1.42	1	1	1.45	1.45
Robust score for AA1 (S_i)	7.4[c]	19.3[a]	5.0	5.0	12.6[b]	7.3
ANN impact (IM_i^{ANN})	31.8	33.9	32.8	25.3	36.1	36.5
Standard deviation for the AA2 $\left(1 + \sum_{j=1}^{3} Std_{i,j} /3\right)$	1.18	1.66	1	1	1.45	1.45
Robust score for the AA2 (AS_i)	63.7[c]	222.9 [a]	32.9	25.3	99.8[b]	56

[a] The most effective policy.
[b] The second most effective policy.
[c] The third most effective policy.

5. Discussion and conclusion

This study investigates the impact of digital transformation's new technology in facilitating policy making (Schwertner, 2017) by considering public transport as a case study. The established research question seeks to understand to what extent can digital transformation be embedded into the policymaking? This particular emphasis on artificial intelligence as a prime example of how new technologies optimise policies made by transportation policymakers (Naumova et al., 2020). More specifically this paper contributes theoretically, methodologically, and empirically to the literature on the policymaking process, highlighting its applications, benefits, challenges, and ethical considerations.

6. Discussion

It was realised that DT is most commonly implied at two organisational levels. Mainly, this is due to the importance of optimising daily operations and cross-functional coordination using advanced digital technologies (Amankwaa et al., 2024; Bansal et al., 2023; Fang and Ju, 2024; Matarazzo et al., 2021; Ooi et al., 2023; Zhu and Li, 2023). The overarching aim is to accelerate knowledge through the use of data-driven insights and make informed decisions. Although DT literature indicated that DT is also applicable at strategic level in terms of supporting and making strategic decisions in the long-term (Amankwaa et al., 2024; Dubey et al., 2024; Keding and Meissner, 2021), it is still understudied (Dalalah and Dalalah, 2023; Holmström and Carroll, 2024; Kohli and Melville, 2019). Hence, this research developed AI-based strategic decision-making framework to address the gap in the literature.

This research focuses on the next generation of the digital technologies commonly referred as the Generative AI tools. The framework considers the implementation of generative AI to inform decisions at the strategic level facilitating knowledge acquisitions from different sources. This framework fits conveniently with the OLT in different aspects. This is because the essence of the traditional OLT focuses on the continuous learning and obtaining knowledge (Agnihotri et al., 2023; Zhang et al., 2021). The contribution of this research builds on that understanding and extends OLT in new era of AI emphasizing the significance of learning and knowledge acquisition through the utilisation of generative AI.

As a methodological contribution a three-phase approach was proposed including hypotheses testing and structural equation modelling, utilising artificial neural network, and finally decision-making. The proposed approach is a viable alternative to be used as a systematic decision-making method for transportation policy making with higher precision outperforming humans' capability in informing accurate decision-making. Furthermore, it may be used as a structural component in generative AI applications for decision-making, adding explainability of observed activities and linking them to decision making at the strategic level.

This paper confirms empirically the expectations of prior research (Craglia, 2020; Kitsios and Kamariotou, 2021) that address the opportunity for integration of DT i.e., AI and its usefulness in policymaking. More precisely, a mix of six transportation policy recommendations was presented to municipal transportation policy executives and decision makers and their views were collected using a follow-up questionnaire. An AI-based approach including three main criteria of cost, feasibility, and impact of policies from the perspective of the policymaker were performed to analyse the impact of each policy on public transport modal choice. The results confirm that social awareness and transportation safety policies were the most impactful in the municipality.

The results of the proposed AI-based methodology confirm that AI can optimise decisions in the same manner as experienced transportation policy makers do. Although this case study focuses in a small municipality and used the framework as a structural enabler of higher order policymaking, the proposed framework has the capability to be generalised across various initiatives and policymakers. This means the framework could be used as a DT tool in developing generative AI at strategic level supporting governmental organisations in making more effective policies.

6.1. Future research

This research provides future directions. The framework was evaluated in the transportation industry for decision-making, however, it can be used more precisely by improving the engine of informed decision-making. As an example, simulation-based optimisation can be embedded with the framework which could lead to enhanced knowledge learning. Additionally, ethical factors can be considered to enhance the applicability of the proposed framework which could lead to more accurate policymaking. The framework and decision-making process are not flawless but to reduce any unprecedented implications, the framework can be modified to fit with the context of the problem or case study. The applicability of the proposed framework on helping humans in policymaking by a machine could be evaluated in another further research. Moreover, human interaction and footprint should be considered within the decision-making process to eliminate the propounded understanding that machines and robots are taking over humans. Another direction could be ethical consideration that may be developed by some strategic issues through the utilisation of the proposed framework.

CRediT authorship contribution statement

Ioannis Koliousis: Resources, Investigation, Data curation, Writing – review & editing, Validation, Conceptualization. **Abdulrahman Al-Surmi:** Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Formal analysis, Conceptualization. **Mahdi Bashiri:** Writing – review & editing, Writing – original draft, Validation,

Methodology, Investigation, Formal analysis, Conceptualization.

Data availability

Data will be made available on request.

Acknowledgments

The authors would like to thank Ms Ioanna Legaki, Ms Ioanna Mantzavinatou, Ms Georgia Syrma, Ms Asimina Panagou, Mr Claus Köllinger and Professor Stratos Papadimitriou as well as Mayor Stavros Tsirmpas for their support and for facilitating the survey. This research has utilised data that were collected as part of the URBACT III funded project "Citymobilnet".

Appendix 1. Measurements

Variables	Items	Sources
Distance	How long is the distance you typically travel for shopping?	(Jochem et al., 2021; Limtanakool et al., 2006)
Time	How long is the travel time for shopping?	Limtanakool et al. (2006)
	How long is the travel time for visits to friends/relatives?	
Problems	Do you consider travel safety to/from schools as a problem?	(Dia H., 2002; Leung et al., 2021; Yang et al., 2016)
	Do you consider travel safety in general (pavements, waiting areas, etc.) as a problem?	
	Do you consider inconvenient routes and frequency of PT as a problem?	
	Do you consider dangerous crossings as a problem?	
	Do you consider lack of footpaths for leisure activities and sports as a problem?	
Frequency	How often do you travel for shopping?	(Jochem et al., 2021; Limtanakool et al., 2006)
	How often do you travel for entertainment?	
	How often do you travel for visits to friends/relatives?	
	How often do you travel for accompanying children to school?	
Quality	Using PT is convenient	(Chee and Fernandez 2013; Rahul and Manoj, 2020)
	PT is the safest travel option	
	Using PT is a satisfying experience	
	There are many stops near me that I can choose from	
	PT is trustworthy	
	There is good level of information regarding PT	
	There are many PT options (bus, metro, train)	
	PT is affordable and at a good price	
Social	I feel that it is my responsibility to use PT	(Pan et al., 2019; Sadri et al., 2021; Sherwin et al., 2014; Wilton et al., 2011)
	Using PT is effective	
	Using PT improves health	
	Most of my friends and relatives use PT	
	Using PT is typical of me	

Appendix 2. Variables Tests

Variables	AVE	CR	CA
Distance	1.0	1.0	1.0
Frequency	0.4	0.7	0.6
Quality	0.4	0.9	0.8
Social	0.4	0.8	0.7
Problems	0.4	0.8	0.7
Time	0.6	0.7	0.5

Appendix 3. Cross Loadings

Items	Distance	Time	Problems	Frequency	Quality	Social
D1	1.0					
T1		0.9				
T2		0.5				
P1			0.6			
P2			0.5			
P3			0.6			
P4			0.8			
P5			0.7			
F1				0.8		
F2				0.6		
F3				0.5		
F4				0.6		
Q1					0.7	
Q2					0.5	

(*continued on next page*)

(*continued*)

Items	Distance	Time	Problems	Frequency	Quality	Social
Q3					0.7	
Q4					0.6	
Q5					0.7	
Q6					0.6	
Q7					0.7	
Q8					0.6	
S1						0.6
S2						0.7
S3						0.5
S4						0.6
S5						0.8

Appendix 4. Mediator Effects

Indirect Path	Path	T Value	P Value
Problems - > MC Quality - > MC Social	0.22	7.57	0.00
Distance - > MC Quality - > MC Social	0.09	2.82	0.01

Appendix 5. Follow-up Data

Policy and decision-maker	Policy	Impact Score ($\boldsymbol{IM_{ik}}$)	Cost Score ($\boldsymbol{CM_{ik}}$)	Feasibility Score ($\boldsymbol{FM_{ik}}$)	Policy Score ($\boldsymbol{PS_i^k}$)
1	PTP1	5	2	1	4
	PTP2	4	3	3	6
	PTP3	5	1	1	2
	PTP4	5	1	1	3
	PTP5	4	2	2	1
	PTP6	5	3	1	5
2	PTP1	4	2	1	5
	PTP2	3	3	4	6
	PTP3	5	1	1	3
	PTP4	5	1	1	2
	PTP5	5	2	2	1
	PTP6	5	1	1	4
3	PTP1	4	2	1	5
	PTP2	2	3	4	6
	PTP3	5	1	1	2
	PTP4	5	1	1	3
	PTP5	5	2	2	1
	PTP6	4	2	1	4
4	PTP1	4	2	1	5
	PTP2	4	3	3	6
	PTP3	5	1	1	2
	PTP4	5	1	1	1
	PTP5	5	2	2	3
	PTP6	5	3	1	4
5	PTP1	5	2	1	6
	PTP2	5	3	2	5
	PTP3	5	1	1	2
	PTP4	5	1	1	1
	PTP5	4	2	2	3
	PTP6	5	3	1	4

Appendix 6. Confirmed Factors

	Distance	Time	Social	Quality	Crisis	Problem
PTP1	0.141	0.165	0.211	0.213	0.348	−0.290
PTP2	0.000	0.000	0.000	0.213	0.348	−0.290
PTP3	0.000	0.000	0.211	0.213	0.348	−0.290
PTP4	0.000	0.165	0.000	0.000	0.348	−0.290
PTP5	0.000	0.165	0.000	0.213	0.348	0.000
PTP6	0.000	0.000	0.000	0.213	0.000	0.290

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