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Personalised passenger information systems in public transport: a review and a 5-level personalisation taxonomy

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ABSTRACT
Providing relevant information to passengers is essential for the functioning of the public transport system. With the digitalisation of passenger information systems (PIS), passengers currently have access to large amounts of information. To avoid cognitive overload among passengers, public transport systems experiment with applying personalisation to PIS, allowing for the provision of tailored information according to the needs and desires of passengers. Notwithstanding, systematic definitions and guidelines for designing personalised PIS in public transport are currently lacking. We, therefore, introduce a framework for assessing the personalisation levels of PIS, to close the gap between theoretical conceptualisations and practical implementations of PIS. Our framework defines five levels of personalisation, which are substantiated by a review of 40 papers focusing on personalisation in PIS .

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Personalization; information systems; public transport; taxonomy; passenger information

1. Introduction

Passenger information systems (PIS) play a key role in public transport, fulfilling the task of informing passengers about the workings of the public transport system. Without accurate and reliable information, passengers may experience confusion, delay, and dissatisfaction with the public transport service (Zurob et al., 2016). Public transport operators, therefore, have incorporated new technologies to improve the accuracy and reliability of PIS. Examples of such technologies are real-time information systems (Zhang et al., 2017), navigation systems (Foell et al., 2014) and algorithms that can generate additional types of passenger information, such as crowding levels in vehicles (Drabicki et al., 2020). With the digital revolution of information systems, PIS have become capable of including a wide range of information content into PIS. However, these large amounts of information also pose challenges for passengers, such as cognitive overload and complex user interactions (Hörold et al., 2022).

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Personalised passenger information has been identified as a solution to facilitate high-quality travel and overcome the challenge of cognitive overload. With personalisation techniques, such as filtering, ranking, and altering the content of passenger information, PIS can become more user-friendly, understandable, and time-efficient. Emerging research on personalisation in PIS has introduced various methods for conceptualising personalised passenger information (Vredenborg et al., 2025). For example, it is possible to utilise automated fare collection (AFC) data to derive passenger preferences and travel patterns, which can be used to personalise route recommendations (Lathia et al., 2013). Another example shows that it is desirable to alter the content of PIS based on the travel phase in which the passengers are travelling, such as before the trip, at a stop, and onboard the vehicle (Zurob et al., 2016). Both examples demonstrate the feasibility of personalising passenger information. However, little is known about the performance quality of different personalisation methods or their impact on passengers' experiences.

A comprehensive framework for comparing PIS performances is missing because of the lack of systematic definitions and guidelines for personalisation in PIS in the public transport domain. To the best of our knowledge, no existing literature classifies personalisation in PIS into a comprehensive taxonomy or a structured framework that encapsulates the interrelationships between different personalisation dimensions. Instead, past research focused on frameworks that aid in analysing and understanding personalisation dimensions in isolation. For example, the study from Reis and Carvalho (2014) was the first to present a conceptual evaluation framework in the form of personalisation levels. This model, however, focuses only on one dimension of personalisation – the object of personalisation. Yet, a comprehensive taxonomy is essential for developing PIS, and classifications can help define the requirements and characteristics needed to achieve desired functionalities.

We introduce a framework for classifying personalisation levels in PIS by synthesising the existing literature on personalisation in public transport. In doing so, we adopt the perspective on automation levels for autonomous driving, as outlined in SAE International (2021), to define the levels of personalisation for PIS in public transport. This analogy was selected because of the shared conceptual framework on allocating roles and responsibilities between humans and systems in executing functionalities. Through the analysis of PIS studies, we seek to understand how personalisation functionalities can vary in their reliance on passenger participation and degree of system autonomy, allowing the identification of what constitutes high and low levels of personalisation.

The remainder of this paper is organised as follows: In section 2, we synthesise the literature on personalised public transport by introducing the dimensions of personalisation. Section 3 presents the analysis of the studies and building blocks for defining personalisation levels for PIS. We then introduce the levels of personalisation and their corresponding characteristics in Section 4. We conclude this study with a research agenda and offer some concluding remarks in sections 5 and 6, respectively.

2. Personalisation in information systems

2.1. Personalisation definition

Defining personalisation is important to determine the searching keywords for the literature review. However, the literature shows no universal definition of personalisation (Fan

& Poole, 2006). Many of these definitions are specific to their application domains. A personalisation definition from user modelling shows a focus on personalisation attributes: "Personalization is a controlled process of adaptation of a service to achieve a particular goal by utilizing the user model and the context of use" (Asif & Krogstie, 2012). Another example from marketing shows a focus on the personalisation process: "Personalization is the combined use of technology and customer information to tailor electronic commerce interactions between a business and each individual customer" (Vesanen, 2007). For this study, the domain is passenger information systems in public transport. Therefore, this study adopts the definition of personalisation in information systems provided by Fan and Poole (2006). According to this definition, "personalization is a process that alters a system's functionality, interface, information access, content, or distinctiveness, aiming to increase its relevance to an individual or a category of individuals".

Additionally, some terms are used interchangeably with personalisation. According to Vredenborg et al. (2025), it is important to distinguish personalisation from customisation, adaptation, segmentation and individualisation. While closely related, customisation refers to allowing users to provide direct and explicit input to the system, typically within a predefined set of options (Fan & Poole, 2006). Compared to personalisation, customisation is more predictable and less intrusive to the user and can be considered a less advanced subset of personalisation, given its need for user participation.

Another closely related term is adaptation. Adaptation refers to a system's properties that automatically adjust to suit the user's needs. Unlike customisation, adaptation serves as a means to achieve personalisation (Fan & Poole, 2006). Adapting information to the needs of passengers is at the core functionality of personalisation. Adaptation should, therefore, be viewed as a characteristic of the system rather than a synonym of personalisation.

Next, segmentation, dividing individuals into distinct groups, is a fundamental practice for personalisation approaches (Bauer & Lasinger, 2014). Segmenting users into different groups based on their shared characteristics, such as demographics, interests, and preferences, facilitates a deeper understanding of the target audience. This, in turn, enables more effective personalisation catering to the specific needs of individuals. When the segmentation process becomes highly granular, to the point of identifying individual users, segmentation is referred to as individualisation (Vredenborg et al., 2025).

2.2. Dimensions of personalisation

Given the ambiguity of personalisation, past research has shifted focus from definitions to developing classification frameworks that aid in understanding various personalisation approaches in information systems. Fan and Poole (2006), introduced a classification scheme for personalisation in information systems, consisting of 3 dimensions: (1) the object of personalisation, (2) the target of personalisation, and (3) the initiator of the personalisation. The object of personalisation can refer to four different aspects of information systems in the situation of information science: content, user interface, communication channel, and functionality. Next, the personalisation target can take on many forms, however they can often be classified into two categories: (1) a single user or (2) a group of users who share one or more characteristics. Third, the initiation of personalisation can be done by: (1) System-initiated personalisation, in which the system automatically applies personalisation, or (2) user-initiated personalisation, where the user provides the trigger that starts the personalisation.

In marketing, this scheme has been extended with additional dimensions, highlighting information technologies and data management approaches important for personalisation (Aksoy et al., 2021). Three additional dimensions relevant to information systems are: (4) the type of input data, (5) the source of the input data, and (6) the trigger for personalisation. In contrast with the dimensions of Fan and Poole (2006), the three additional dimensions have no fixed set of dimension characteristics. For example, personalisation can be based on various data types coming from multiple sources, such as sensory data or survey data. There are recurring categories of data and data sources, however, the range is rather diverse and not limited to those categories.

2.3. Analysis of personalisation dimensions in PIS

As stated before, this study aims to identify a taxonomy for personalisation in PIS, based on the conceptual framework employed in defining the levels of autonomous driving automation. In the report of SAE International (2021), the levels of automation are determined by allocating roles and responsibilities for driving functionalities between the human driver and the driving automation system. The report highlights the importance of understanding specific functionalities involved in driving systems and the operating characteristics of these functionalities when allocating the roles and responsibilities to either the user or the system.

To adopt this method to the situation of personalisation, the proposed framework will define personalisation levels based on a comprehensive analysis of the core functionalities involved in personalising PIS. Moreover, the analysis will examine the operational characteristics of these functionalities in terms of the dimensions of personalisation, which will assess the degree of passenger participation required to execute the functionalities. The resulting insights will then be used to define different levels of personalisation for PIS based on the degree of passenger participation required. For example, at lower levels of personalisation, user agency takes precedence, as passengers actively personalise their experience by manually inputting preferences or interpreting the relevance of provided information. Conversely, at a higher level of personalisation, the system autonomy becomes the driving force, with advanced PIS leveraging automation and adaptive technologies to personalise information tailored to individual passenger needs. As the functionalities of PIS evolve when automation is more prevalent, shifts in the balance between user agency and system autonomy can be observed, with changes in the system's functionalities influencing the extent to which passengers can make choices regarding the personalisation of their passenger information. These shifts serve as cut-off points for classification, enabling the identification of different levels. This structured approach provides a framework for systematically evaluating the functionalities of PIS to determine the different levels of personalisation.

2.3.1. Literature search strategy

To identify the core functionalities and operational characteristics of personalisation in PIS, we conduct a systematic literature review, analysing studies that implement personalisation in PIS. Studies are excluded if they either meet any exclusion criteria or fail to satisfy all the inclusion criteria:

Inclusion criteria

- **I1:** The study showcases a case study or prototype focused on the provision of passenger information.
- **I2:** The study presents a conceptualisation of personalisation.
- **I3:** The study is targeted at the public transport domain.
- **I4:** The study presents a unique conceptualisation of personalisation in the context of this study.

Exclusion criteria

- **E1:** Personalisation is not conceptualised.
- **E2:** Personalisation is not mentioned as part of the case study.
- **E3:** The study is not targeted at passenger information systems.
- **E4:** The paper is not in English.
- **E5:** The paper is dated before 2010.
- **E6:** The paper is not peer-reviewed.

Each study that meets our predefined criteria is examined using a set of questions designed to capture personalisation. These dimensions indicate varying levels of passenger participation, some represent active input, while others function with minimal or no passenger involvement. By systematically linking the values of these dimensions to specific personalisation functionalities, we assess whether each functionality demands high or low passenger participation. This approach allows us to determine how different personalisation strategies impact the role of passengers in the system. We pose the following questions in our investigation:

- What are the functionalities of the PIS aimed at fulfilling the objective of personalisation?
- What is the object of personalisation?
- Who is the target of personalisation?
- Who initiates the personalisation?
- What types of input data are used for the personalisation?
- What are the sources of the input data?
- What triggers the personalisation?

For the systematic literature review, studies published from 2010 onward are reviewed. This time frame was selected due to the advancement of PIS and the broader digital revolution initiated by the introduction of smartphones. To identify relevant studies, three digital databases were used: (1) Scopus, (2) the KTH Library discovery interface, and (3) the ACM Digital Library. Scopus was chosen for its broad disciplinary coverage, while ACM was included due to its strength in Human–Computer Interaction (HCI) research, which often addresses PIS as a practical application area. The KTH Library interface was used as a supportive exploratory tool; its AI-assisted features helped refine the search process and uncover relevant literature beyond traditional keyword searches. A structured search query was formulated as part of the process, consisting of three components.

1. ("personalization" OR "personalized" OR "adaptive" OR "individualized" OR "customization")
2. ("passenger information*" OR "travel information*" OR "transport information*" OR "recommendation system*")
3. ("public transport" OR "mass transit")

The search, last performed on 13 January 2025, resulted in a combination of 173 studies. After applying the inclusion and exclusion criteria, a total of 40 papers were retained. These 40 studies have been carefully read and analysed. The results of this search are presented in Table A1.

2.3.2. Overview of personalisation in PIS

The results in Table A1 were used to synthesise levels of personalisation in PIS by classifying functionalities based on personalisation dimensions. By listing the studies in a table, we could examine various PIS functionalities and link them to personalisation characteristics. The table provides an overview of each study, including author, year, country, and personalisation details. It also examines how each study aligns with the personalisation dimensions outlined in Section 2.3.1, offering insights into the need for passenger participation in personalisation.

Based on the systematic literature review, we identify several trends in PIS implementations with regard to personalisation. One of the main trends observed is the growing focus on personalisation in PIS. The average number of studies on personalisation in PIS per year is higher between 2020–2024 (3.2 studies/year) than between 2010–2019 (2.4 studies/year). Another trend can be found in the locations of the studies. The majority of studies focus on countries in the Global North, with only a limited number examining locations in the Global South. Additionally, most research is centred on urban areas, particularly cities, which aligns with the higher development and availability of public transport infrastructure in these regions compared to rural areas.

The personalisation dimensions show no trends can be identified regarding the object and initiator of the personalisation. Studies differ on whether content, interface, communication channel, or functionality should be personalised, though content is the most common focus. Four content types are typically personalised: travel information, route recommendations, travel plans, and navigation. These four types of personalised content serve distinct purposes in supporting and enhancing the passenger experience. Travel information consists of individual, context-specific data points, such as service disruptions, arrival times, or fare details. Route recommendations aggregate multiple pieces of information to suggest efficient paths between locations. Travel plans represent a broader, more strategic form of content, offering structured, often multi-day itineraries that aim to support long-term travel behaviour improvement. Navigation, meanwhile, provides the most detailed, moment-to-moment guidance, helping users follow a selected route in real time and adjust dynamically to any changes during the journey. Moreover, most studies involve user-initiated personalisation (64%), although the aim is often to minimise user input. Notably, system-initiated personalisation dominated from 2011–2013, reflecting an ongoing evolution in the field and uncertainty about the optimal personalisation strategy.

This inconclusiveness underscores the need for systematic definitions and guidelines for personalisation in PIS. With the growing number of studies on personalisation in PIS over the past five years and the diverse implementations of personalisation, the need to be able to systematically compare these implementations has become increasingly important. This is crucial to identify the most effective approaches to personalising passenger information.

3. Core functionalities of personalisation in passenger information systems

The first step in defining personalisation levels is to identify the core functionalities of personalisation in PIS. Clusters can be identified from the functionalities present in the personalised PIS, as shown in Table 1. In this analysis, the focus for functionalities was on how the output of each functionality contributes to improving the relevance of passenger information to an individual or group of individuals (Fan & Poole, 2006). Consequently, only functionalities that contribute to the filtering, ranking, altering, or modifying of the content or representation of passenger information are considered.

We used a threshold of 20% for identifying core functionalities. That is, a functionality is considered to be core if it was present in at least 20% of the studies. Using this approach, three core functionalities are identified: (1) the ability to identify the target of personalisation, (2) the ability to be aware of travel situations, and (3) the ability to determine the trigger for information provision. We discuss those in the subsequent subsections.

3.1. Target identification

The most common functionality of personalisation in PIS is identifying the target of personalisation. This cluster represents functionalities such as the processing of user preferences and the generation of user profiles, which are later used to personalise passenger information. This is expected, as personalisation requires an understanding of the target to focus on improving the personal relevance of passenger information to an individual or group of individuals (Fan & Poole, 2006). The reviewed studies demonstrate a range of techniques and methods utilised to identify the characteristics of a personalisation target in PIS. We categorise the techniques and methods based on the degree of passenger participation required. The following categories of target identification approaches are identified in Table 2.

The categorisation indicates that the available input data shapes the need for passenger participation in target identification. When automated data collection is lacking, the

Table 1. Frequency of each functionality category.

Functionality category/cluster	Frequency	%
Ability to identify the target of personalisation	38	95
Ability to be aware of travel situations	29	72
Ability to determine trigger for provision	14	35
Ability to connect with infrastructure in public transport network	6	15
Ability to collect feedback from passenger	3	7

Table 2. Target identification categories.

Name	Definition	Common indicators	Example
No Target	No target refers to the lack of segmentation among passengers when providing passenger information. All passengers receive identical information without considering there to be individual differences in information needs.	• Static information that cannot be altered • Information covers the whole network at once	A public transport map showing all transfer possibilities in the system.
Geo-temporal Constraints	Geo-temporal constraints refer to passenger segmentation based on spatial and temporal constraints of a passenger for a certain trip.	• Search query to find route recommendations • List of departure times at one specific station • Filters to indicate preference for a limited set of system attributes	An app that suggests a route recommendation based on the origin and destination filled in the search query.
Stated User Preferences	Stated user preferences refer to passenger segmentation based on one-time explicit input from the passenger about their travel preferences, which the system stores and uses to personalise information.	• User-submitted preferences like preferred transport modes or accessibility needs • Initial onboarding questions when opening the app for the first time • Marking stations or routes as favourites	An application shows the departure time of your favourite stations on the homepage of the application.
Revealed User Preferences	Revealed user preferences refer to passenger segmentation based on the passenger's historical travel behaviour and records known by the system.	• Data from ticketing systems or travel cards (AFC) • Inferred attributes derived from machine learning models • Assigning passengers to clusters or general passenger profiles	A transit system recommending the best departure time from home for the passenger based on the passenger's recorded temporal travel patterns.
Projected User Preferences	Projected user preferences refer to passenger segmentation based on predicted individual preferences based on the system's interpretation of the passenger.	• Unique passenger profiles for every passenger • Multiple input data sources beyond AFC • Ability to personalise for new or unknown travel situations	A public transport app that suggests a route for a new destination to which the passenger has never travelled before.

personalisation process relies heavily on explicit user inputs to determine user preferences. For this reason, higher levels of personalisation should include automated processing of input data regarding the target.

3.2. Situational awareness

The second functionality cluster is the system's ability to be situational aware. This cluster represents functionalities such as the processing of the trip's situation or the status of the public transport network. Additionally, the cluster represents the functionality of detecting and locating passengers, as this information is necessary to determine the situation in which the passenger currently is. According to Vredenborg et al. (2025), a diverse set of attributes can be considered for the personalisation of passenger information. The reviewed studies demonstrate a range of attributes, including trip, system and passenger characteristics. We categorise these attributes based on the degree of passenger participation required. The following categories of situational awareness attributes are proposed in Table 3.

The categorisation implies that the need for passenger participation in the creation of situational awareness is shaped by the number of sources for the input data and the way these sources are connected to the PIS. The situational awareness that solely relies on historical trends requires the passenger to input their travel situations to understand the demand side, but with higher levels of situational awareness, the system can automatically sense the travel situation by combining multiple different types of sources. For this reason, higher levels of personalisation should be able to leverage multiple sources of data for situational awareness to automatically incorporate accurate situational awareness.

3.3. Trigger of provision

The third functionality cluster is the trigger of provision. This cluster represents functionalities that focus on the timing of the provision of passenger information and showcase various examples of provision triggers. Provision triggers refer to the events that cause the information to be presented to the passenger. The reviewed studies demonstrate a range of triggers and we categorise these triggers based on the degree of passenger participation required. The following categories of provision triggers are identified in Table 4.

Higher levels of personalisation should allow for more proactive information provision, as the system anticipates the passengers' needs and provides them with the right information before they explicitly signal their needs.

4. Levels of personalisation

With the core functionalities and their categories identified, we can now outline a framework for levels of personalisation. This framework, inspired by the levels of driving automation (SAE International, 2021), illustrates a decreasing need for passenger participation across five defined levels of personalisation. Figure 1 presents these five levels. The three core functionalities introduced in the previous section are represented as columns, with their respective categories arranged according to the degree of passenger participation each requires. The rows denote the personalisation levels, ranging from Level 0: No Personalisation to Level 4: Full Automation, and include intermediate stages: Level 1: Customisation, Level 2: Partial Personalisation, and Level 3: Conditional Automation.

This framework serves a dual purpose: it can be used as a design guideline for developing new PIS and as an evaluation tool for assessing existing systems. In the design context, it helps determine the appropriate functionalities by providing representative configurations of attributes commonly implemented when aiming to achieve a level of personalisation. As an evaluation tool, it provides a structured way to classify and compare existing PIS based on the degree of passenger involvement they require. A

Table 3. Situational awareness categories.

Name	Definition	Common indicators	Example
No Awareness	A system with no awareness delivers information in a fixed or generic format, regardless of changes in the environment or user context. It assumes that all passengers have identical needs and therefore can receive the same information.	• Static schedules or content • No integration of real-time data feeds • No variation in output based on user or system state	A printed timetable at a station.
Historical Awareness	A historically aware system utilises previously recorded data about the transport network to identify patterns, trends, or expected conditions. The data is often analysed manually by the developers behind the PIS as the system lacks sophisticated processing functionalities for this kind of task.	• Historical time windows (e.g. peak hours, weekends) • Aggregated data over longer periods of time (average walking speed, transfer times, crowding levels) • Categorical labels (crowding: high/low)	A trip planner that provides passengers with crowding data for a "typical" Tuesday at 8 AM, using archived data to estimate the crowding levels.
Supply Awareness	Supply awareness describes a system's ability to detect and react to the real-time operational state of the public transport network. The focus is on the "supply side" which shapes the availability of travel options.	• Real-time data feeds from vehicles (e.g. GTFS-RT, AVL) • Automatic information updates in the system for service disruptions or changes • Dynamic journey re-planning based on network state	Route recommendations with updated departure times based on the real-time location of the vehicle.
Demand Awareness	A demand-aware system incorporates real-time data about the individual passenger's location, behaviour, or preferences.	• Use of location services from passenger devices • Trip-phase inference • Individual-level data regarding travel behaviour	A mobile app that notifies a passenger to hurry because their connecting train is departing soon from a nearby platform, and the passenger is not at the platform yet.
Ecosystem Awareness	Ecosystem awareness refers to a system's ability to perceive and integrate information about the broader environmental and societal context in which public transport operates.	• Weather APIs or local forecasts integrated into route planning • Calendar or event-based data (e.g. holidays, concerts) • Alerts about local emergencies showing to avoid a certain area	A PIS that suggests avoiding a transit hub due to congestion caused by a nearby football match, and instead recommends a walk because it is good weather.

key assumption underlying both purposes is that the object of personalisation is pre-defined during the problem definition phase and remains fixed. This assumption ensures the framework can be applied consistently across different use cases.

Each level (row) in the framework comprises a typical combination of one category from each of the three core functionalities, reflecting a representative configuration for that level of personalisation. These combinations serve as practical guidelines. In the design phase, they indicate how functionalities should operate to reduce the need for passengers, while in the evaluation phase, they support the identification of alignment or mismatch between implemented features and intended personalisation goals.

Table 4. Trigger of provision categories.

Name	Definition	Common indicators	Example
User Trigger	User trigger refers to a PIS interface where the passenger must actively initiate the provision of information by explicitly requesting or searching for it.	• Manual use of search functions or menu navigation • Information is only displayed following a user action • No automatic or proactive communication from the system	A passenger opens a transit app and searches for the next train departure from their current location to a specific destination.
Supply Trigger	Supply trigger refers to a PIS interface where operational events in the transport system, such as disruptions or delays, automatically update the information after this is manually requested by the passenger.	• Notifications triggered by real-time events • Updates shown only after a user engages • Real-time monitoring of supply-side events	After a user looks up a journey, they receive an alert within the app that a delay has occurred on their planned route.
System Trigger	System trigger refers to a PIS interface where the system autonomously decides to deliver information to the passenger without any explicit request, based on predicted or inferred travel intentions.	• Proactive alerts about upcoming transfers or delays • Push notifications tailored to the user's trip • Continuous background monitoring	A passenger receives a notification reminding them to leave earlier due to a disruption, without opening the app.

To strengthen its credibility and practical relevance, the framework was iteratively evaluated during its development through engagement with domain experts. Multiple workshops were conducted with disruption information specialists from Stockholm's public transport operator. These sessions included participants with diverse roles, such as project managers, UX designers, and smart card data analysts, ensuring a multifaceted understanding of passenger information needs. To broaden the scope of validation, we also conducted interviews with passenger information system managers and smart mobility experts from the City of Stockholm. This collaborative and stakeholder-informed process helped ensure that the framework is grounded in practical considerations and reflects the real-world challenges and expectations related to personalisation in PIS.

4.1. Level 0: no personalisation

At level 0, personalisation is absent. Here, the system operates uniformly for all passengers, offering a standardised experience characterised by passengers actively monitoring the search for passenger information. Situational awareness or passenger preferences are not considered, and information is only accessible when explicitly requested by the user. Example PIS for this level are printed timetables or static journey information offered through a website.

4.2. Level 1: customisation

At level 1, the passenger is given the option to customise the passenger information to achieve personalisation. Customisation refers to allowing users to provide direct and explicit

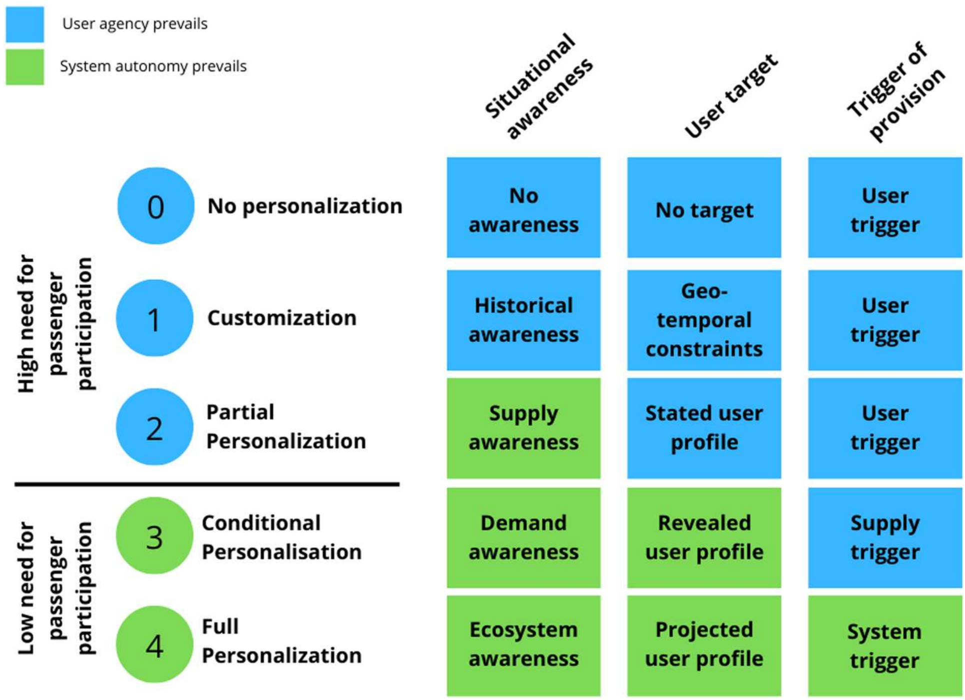

Figure 1. Framework for levels of personalisation.

input to the system and can be characterised by the passenger actively contributing to achieving the personalisation. The system, on the other hand, remains passive and executes exactly what is requested based on the user input.

Typically, level 1 PIS provides limited, developer-defined customisation options, requiring passengers to manually input preferences. These limitations highlight the need for passenger participation, as passengers must actively seek out the desired information. Many applications of public transport operators fall under this level, as they allow the passenger to apply constraints to route recommendations, such as the maximum number of transfers or the maximum walking distance to and from a station. Examples of level 1 PIS are the web applications of Stockholm Lokaltrafik in Sweden and 9292.nl in the Netherlands. These systems do not proactively make decisions based on those constraints; rather, they only incorporate them when the passenger explicitly requests a journey option.

Where many PIS apply the same constraints in their application, there are in practice no limitations on the attributes that can be used as constraints. As long as developers can programme the operational rules coming with the constraints, any attribute can serve as a constraint for customisation. An example of this is provided by Chowdhury and Giacaman (2015). In their PIS, passengers can customise the functionalities they wish the system to include. Here, the customisation is not focused on the content, but on the user interface of the PIS.

4.3. Level 2: partial personalisation

At level 2, systems provide partial personalisation by automating functions for general trips. General trips refer to travel situations that take up a large portion of the passenger's trips and could therefore be labelled as the default travel situation of the passenger. Partial personalisation refers to systems that personalise based on assumptions derived from the general trips because of simplified functionalities or a lack of data on unique travel situations. As a result, they offer less accurate, less complex personalisation and apply only to general trips. Situational awareness, for example, can be simplified because of fixed attributes for travel situations, despite the many influential factors involved (Keller et al., 2020). Therefore, the personalisation sticks to only the default travel situation, lacking the necessary depth to be relevant for a specific travel situation.

Furthermore, functionalities focusing on the identification of the target make use of stated preferences to simplify their operations. By asking the passenger to provide their preferences, PIS evade the need for complex methods that would derive the same preferences. Instead, they apply simple questionnaires (Bajaj et al., 2015; Ceder & Jiang, 2019; Herzog et al., 2017). However, one limitation of this approach is that stated preferences often take a lot of time, reducing the number of travel situations that can be covered. As a result, the input data is limited and lacking insights for a detailed analysis of individual user preferences in specific travel situations.

Multiple review studies in Table A1 showcase partial personalisation. One good example is provided by Al-Rahamneh et al. (2021). Their proposed PIS ask passengers to state their travel preferences which are then processed by the PIS into general user preferences for the user profile. Then, the PIS uses its available sensory data from the city of Pamplona, Spain, to provide personalised route recommendations that fit the user's preferences. As the PIS makes use of only sensory data, the personalisation is limited to the environmental-oriented preferences. Nevertheless, due to the high quality of the sensory data, the PIS can provide accurate recommendations that benefit the user. This study shows that the high-quality data can make up for limitations in the diversity of input data. Another good example is provided by Ceder and Jiang (2019) . Their proposed PIS requires the passengers to explicitly state their user preferences in the form of weights for the attributes used for the personalisation. Compared to Al-Rahamneh et al. (2021), Ceder and Jiang (2019) formulates their stated preferences in such a way that not only the preferences get identified, but also the importance of the preferences. This approach improves the personalisation, as the accuracy of the personalisation increases. This study shows that the formulation of the stated preferences can influence the quality of the data.

Additionally, the reviewed studies revealed that the use of stated user preferences is not a consistent practice across all studies classified as partial personalisation. Where Al-Rahamneh et al. (2021) and Ceder and Jiang (2019) apply stated preferences at the core of their functionality, there were also studies found that utilise stated preferences only during initial interactions to mitigate the "cold start" problem faced by models and algorithms attempting to infer user preferences from historical travel behaviour data (Campigotto et al., 2017; Wang et al., 2024). However, all are classified as partial personalisation as they rely on explicit user input for the personalisation.

4.4. Level 3: conditional personalisation

At level 3, the system automates the functionalities of personalisation for specific, previously recorded travel situations. Unlike partial personalisation, conditional personalisation can handle complex operations and diverse data inputs, incorporating both supply-side (e.g. network features) and demand-side (e.g. trip patterns) factors. An example of this is provided by Jenelius (2020), who proposes a PIS for the city of Stockholm that provides personalised crowding information based on a combination of real-time AVL data and real-time location of the passenger. However, a PIS at this level still needs passenger input in case of new, unrecorded travel situations or in case of unconventional travel situations which are difficult to process from a system perspective. Examples of these situations are cases where the normal assumptions do not apply anymore, such as denied boarding and large-scale system breakdowns.

Moreover, the identification of targets is now determined by revealed user preferences, typically derived from historical travel data. One PIS showcasing this is the PIS proposed by Nakamura et al. (2016), which uses the smart-card data of Fukuoka to model both the supply and demand of the public transport network. Because historical travel data revealed preferences in a situation, the identification of the target goes beyond general user preferences. By linking the behaviour choice of passengers to a travel situation, revealed preferences include specific user preferences for specific travel situations. An example of this functionality can be found in Borodinov and Myasnikov (2020), where preferences are determined per travel activity.

Greater system autonomy enhances the ability to detect travel situations and user preferences, enabling automated information delivery. By analysing and labelling travel situations, the system can identify relevant triggers linked to the preferences of the passenger. When a trigger is found, the system can automatically send relevant information to the passenger. One example of a PIS showcasing this functionality is the proposed PIS of Naumann and Wolf (2011), which sends personalised travel alerts in case of a disrupted journey on relevant routes. Note that the system still relies on the public transport network for the trigger. Only when a certain event or action happens in the public transport network, a trigger can be detected by the system. Another limitation is the system's reliance on historical data. The system can only apply personalisation to travel situations that have been detected before. In the case of new travel situations, the system cannot rely on the assumptions it has created based on historical data. Therefore, the passenger must step in under new travel situations.

Multiple review studies in Table A1 showcase conditional personalisation. One good example of conditional personalisation is the PIS called Navi, designed by Aguiar et al. (2012). Navi uses electronic ticketing infrastructure as a personalised location sensor and provide personalised travel information based on the location of the passenger. Every time the passengers validate their location, by validating the electronic ticket, Navi shares information on how to proceed with the travel. The proactive functionalities focusing on en-route travel information, driven by the system's autonomy, makes Navi a good example of conditional personalisation. Minimal participation of the passenger is needed to receive relevant information at the right time. The only action that is required of the passenger is to fill in the destination of interest before the start of the trip.

4.5. Level 4: full personalisation

At the highest level of personalisation, level 4, the system automates all personalisation functionalities in all known travel situations and uses external data sources to automate all functionalities for travel situations where travel data is missing, as far the external data sources reach. By including external data sources in the personalisation, the personalisation can be based on a richer profile of the passenger. Gaps in travel data coming from smart card data can be filled with external data, resulting in a fully automated system for the passenger that can provide personalised passenger information for all travel situations. To accomplish a rich passenger profile, the system needs to go beyond merely tracking historical data and start inferring passenger preferences and characteristics from different data sources and the passenger's current location. The type of preferences and characteristics that can be inferred depends on the type of external data that is used. Futuristic examples are calendars to learn the activity patterns of the passenger, smart watches to keep track of the passenger's physical state or social media interactions to learn about the passenger's attitude towards public transport and other modes of transport.

A more practical approach to full personalisation is the use of collective filtering. Currently, researchers rely on techniques such as collaborative filtering to determine the relevance of information in unknown travel situations by comparing information and preferences between passengers with similar travel patterns. Examples of PIS applying collective filtering are Herzog et al. (2017) and Li et al. (2023). In their papers, they analyse travel patterns of larger groups of passengers to identify the information needs of an individual target in unfamiliar travel situations. Passengers with similar travel behaviour are assumed to have similar information needs. In this way, collaborative filtering could fill in the gaps left by the historical travel data of the individual target.

PIS classified as full personalisation also have the ability to proactively determine when passengers need information, as it can infer triggers for provision from their own internal analysis. Examples of PIS with proactive information provision are provided by Sottile et al. (2021) and Nakamura et al. (2016). Both papers introduce PIS that proactively generate personalised travel plans to stimulate sustainable travel behaviour based on users' historical travel behaviour.

While the passenger profile attributes depend on the available data sources, it is possible that some essential personalisation attributes may be missing. Therefore, it is crucial to allow passengers to provide their own input to the system. Hopefully, as the external data sources become more comprehensive, this input will become less necessary, encompassing all the essential attributes needed for personalisation. Passenger input for consent should of course always depend on manual passenger input, to ensure that the passenger gives permission to use personal data to personalise.

4.6. Practical implementation of the proposed framework

While the personalisation levels may initially appear as a linear progression, the development of personalisation in PIS is often uneven. In practice, a system may demonstrate advanced personalisation in one functionality, while remaining underdeveloped in the other two. This uneven development complicates the assignment of a system's overall personalisation level based solely on the performance of a single functionality.

To provide a structured method for evaluation, this study introduces evaluation steps for determining a PIS's overall personalisation level. These steps ensure that assessments are grounded in observed system capabilities and account for inconsistencies or uncertainties.

4.6.1. Evaluation steps

- Step 1: Attribute Assessment
  Each core functionality should first be assessed against the defined personalisation levels. This step involves matching the observed attributes of each functionality with the common indicators identified in the categories of the different functionalities.
- Step 2: Uncertainty Handling
  In cases where it is unclear which level a functionality belongs to, due to incomplete documentation, ambiguous user interactions, or evolving system features, the evaluator should aim for the lower level, by relying on the backward compatibility of the levels. This step reduces subjectivity and maintains evaluation integrity.
- Step 3: Consistency Check
  Once the individual personalisation levels of all three functionalities are identified, check whether they align at the same level of personalisation. If all functionalities meet the requirements of the same level, this level becomes the system's overall personalisation level.
  In case the assigned levels of the functionalities do not align with each other, the minimum capability assignment rule has to be met.
- Step 4: Minimum Capability Assignment
- If the functionalities fall into different levels, the system's overall level of personalisation is determined by the lowest-performing functionality, identified in step 1. This conservative approach relies on the backward compatibility of the levels, meaning high-level personalisation functionalities always include the lower level functionalities. Moreover, this ensures that uneven development does not lead to an overestimation of personalisation quality.

4.6.2. Case study: SL, Stockholm

To demonstrate how the evaluation operates in practice, we apply it to the SL public transport mobile application (SL, 2025), which provides real-time route recommendations based on customisable travel options through user input.

- **Step 1: Attribute Assessment**
  Each functionality was evaluated based on its alignment with defined personalisation attributes (Table 5):
- **Step 2: Uncertainty Handling**
  Situational awareness includes demand-related attributes (e.g. crowding information), which might suggest level 3 characteristics. However, because it is unclear whether this information is personalised to the passenger's specific journey or merely general, the evaluation defers to level 2, in accordance with the uncertainty-handling step.
- **Step 3: Consistency Check**
  The functionalities are not aligned at the same level. Situational awareness and timing of provision both reach level 2, while target identification is limited to level 1. Therefore, consistency is not achieved.

Table 5. Case study: results of attribute assessment.

Core functionality	Assigned level	Justification
Situational Awareness	Level 2	Real-time vehicle data provided automatically; also includes general crowding info, though not user-specific.
Timing of Provision	Level 2	Requires the passenger to open the app to receive current information.
Target Identification	Level 1	Heavily reliant on manual input – users must specify destination and filters without system-driven personalisation.

- **Step 4: Minimum Capability Assignment**
  Since target identification is at level 1 and there is no compelling justification to override this classification, the overall personalisation level of the system is assigned as level 1.

As a final assessment, the SL mobile application's PIS demonstrates personalisation in the form of customisation (level 1). However, the PIS shows stronger performance in situational awareness and timing of provision. SL therefore, has the potential of reaching partial personalisation (level 2) by including more automation in the functionality of target identification, thereby reducing the need for passenger participation in the identification of the target.

5. Research agenda

The main objective of the framework is to provide systematic definitions and guidelines for personalisation so that researchers and stakeholders working on developing and implementing personalisation into PIS understand the requirements for their designs. In the following, we explore various perspectives on how personalisation levels can inform and facilitate the development of personalisation in PIS.

The main objective of the framework is to provide systematic definitions and guidelines for personalisation so that researchers and stakeholders working on developing and implementing personalisation into PIS understand the requirements for their designs. Based on our first findings, we have been able to identify several topics that require attention in future research in order to make higher levels of personalisation more common feasible. In the following sections, we describe common technical, operational and social challenges related to PIS and personalisation.

5.1. Data sharing; challenges with storage and management

To gain a more comprehensive understanding of passengers and their travel situations, a large amount of data must be collected. While smart card data gathered by public transport operators is often seen as the ideal resource, it often lacks all the necessary attributes to personalise information based on relevance. As a result, personalised PIS typically import additional data from external sources, expanding the dataset with all the information required for personalisation. However, these data sharing practices face numerous challenges (TRB, 2020). One of the most pressing challenges regarding data sharing is data storage. Currently, data related to public transport is often stored in different locations, causing the responsibility for data sharing to be fragmented across various staff in different organisations (TRB, 2020). The decentralised storage of relevant data makes accessing and managing data for personalised information services complicated and labour-intensive, as every organisation can use its own formatting and rules when handling data.

Different solutions have been proposed to tackle the fragmented data storage. A common solution focuses on the creation of data sharing platforms or dashboards that serve as a centralised point for the different actors to exchange and store data (Al-Rahamneh et al., 2021; TRB, 2020) . Once agreed upon a collaboration, different actors can exchange data on these platforms, which takes care of data storage and management tasks such as data acquisition, data ingestion, stream processing, data processing and data visualisation. Additional benefits of such a platform is that the use of a single platform ensures a common understanding of data formats and definitions, thereby overcoming the problem of data heterogeneity. Data sharing platforms would be beneficial for PIS that require various attributes to execute the personalisation, such as real-time vehicle location and crowding levels, or even environmental information on weather conditions or special events happening in the area. Designers aiming to implement level 3 or 4 personalisation in PIS therefore, should simultaneously push for the development of a data sharing platform. However, there are currently only a limited number of examples of data sharing platforms focusing on the context of personalisation. Future research should therefore focus on the creation of these platforms with the functionalities of level 3 and 4 personalisation in mind.

5.2. The operational considerations underlying data collection and processing

The success of personalisation in PIS depends on the quality of the data. For data to be meaningful, the data collection must be performed with a clear vision of the analysis in mind. For example, it is important to know upfront which attributes should be included in the data and how different attributes relate to each other. Unfortunately, the smart card data collected by public transport operators often lacks this analytical vision, as the focus of the data collection is on operational aspects of the public transport system, rather than data analysis (TRB, 2020). This complicates using smart card data for personalisation purposes, as the smart card data lacks the attributes and relationships needed to personalise according to the passenger's needs and preferences. For instance, smart card data is typically collected in the form of trip legs rather than complete trips, where each check-in with the smart card registers a new leg, making it difficult to connect them into a full journey. The lack of demand-oriented situational awareness makes it challenging to get a complete overview of the entire trip, including origin and destination.

Machine learning models and artificial intelligence algorithms can be potentially used to derive additional attributes and relationships from smart card data, helping to overcome the limitations mentioned previously (Cats, 2024). For instance, machine learning can cluster individual trip legs by their temporal or spatial–temporal patterns, which can then be used to infer personal characteristics of the passenger based on well-studied relationships between these patterns and characteristics. Examples include inferring employment statuses from commuter patterns (Pieroni et al., 2021) and inferring trip purposes of trips performed during the week from spatial–temporal patterns (Cats & Ferranti, 2022). However, current models and algorithms are not yet able to infer all the attributes needed to fully personalise passenger information. In particular, attributes and relationships regarding passengers' socio-demographic information are underrepresented in these studies (Cats, 2024). Therefore, it is difficult to infer characteristics such as the travel companion, physical state or emotional state of the passenger, while these attributes are known to influence the information needs of passengers.

Future research should focus on developing data collection methods that capture attributes related to passenger backgrounds and socio-demographics and allow them to be connected the passengers' travel patterns. Smartphones carried by passengers can play an important role in these data collection strategies. Smartphone-based sensing can track people's travel behaviour and ask passengers about their travel motivations in the same moment (Servizi et al., 2021). An example where smartphone-based sensing is put into practice for this goal is the TRavelVU (Ek et al., 2018). Their application allows for inferring characteristics about the passenger by collecting travel data with the smartphone sensors. This data can also be used to personalise passenger information when included in the system structure of a PIS.

5.3. Ethical considerations and user control

The paper has established a systematic framework for categorising personalisation levels in PIS. However, a key question that emerges is the degree to which passengers are willing to accept various levels of personalisation. While the framework highlights the potential role divisions between the system and the passenger, it lacks insight into the level of system autonomy that passengers are comfortable with. Not all passengers may feel at ease with highly automated personalisation in PIS, as research has shown that ethical issues can arise when users are extensively modelled by such systems (Herder & Masthoff, 2024), which is a concern with the higher levels of personalisation outlined in this framework.

To mitigate ethical issues, it is essential to follow the notion of responsible user modelling (Herder & Masthoff, 2024). Large-scale personalisation may unintentionally or intentionally disadvantage particular users or user groups across multiple aspects, which can reduce the fairness of the system (Konstan & Terveen, 2021). Especially in higher levels of personalisation, where passengers do not all receive the same information, it is crucial to discuss the biases present in the data, to ensure that the data is representative for all. A key strategy is to empower users with control over the personalisation process, granting them ownership of the data collected about themselves and the ability to remove or correct any inferences made by the system. This could be a strategy to increase the acceptance rates of personalisation.

However, enhancing user control over the personalisation process would necessitate increased passenger participation, potentially diminishing the higher levels of personalisation. More research is necessary to determine how user control could be integrated into the higher levels of personalisation without affecting the system's autonomy in the execution of the personalisation functionalities. Currently, the notion of responsible user modelling is not integrated into the levels of personalisation, but more research on the functionalities of personalisation could identify additional core functionalities for personalisation regarding responsible user modelling, which in turn can enrich the framework for the levels of personalisation.

Another important ethical consideration is digital inequality. As digitalisation becomes more prevalent, passengers are increasingly required to possess digital skills to interact with PIS and access relevant information. Research indicates that digital competencies vary significantly among passengers, leading to reduced accessibility for those with lower levels of digital literacy (Durand, 2025). With the introduction of advanced personalisation features, there is a growing risk that PIS will become even more dependent on users' digital skills. To mitigate this risk and ensure equitable access, the design of personalised PIS interfaces should prioritise inclusivity and aim to minimise the need for advanced digital skills. Future research on inclusive design in the context of personalised PIS is essential to identify strategies for integrating personalisation without excluding passenger groups based on their digital capabilities.

6. Closing remarks

Based on the analysis of the literature on implementations of personalisation conceptualisations, we identify the core functionalities of personalisation in PIS in public transport and propose to systematically structure them in the form of levels of personalisation. The five levels of personalisation introduced in this study contribute to the existing knowledge of personalisation in public transport by introducing a hierarchy to the different conceptualisations of personalisation known in this field of research. Admittedly, personalisation can be viewed from different perspectives, as it encompasses many aspects, as shown by the dimensions of personalisation. We choose to conceptualise the levels of personalisation from the perspective of the need for passenger participation. However, there may be alternative conceptualisations of personalisation levels, where different aspects or dimensions of personalisation might lead to different levels of personalisation, as shown by Reis and Carvalho (2014). The proposed levels of personalisation were developed with the intent of addressing key challenges facing the public transport field of research. Specifically, the perspective adopted was that higher levels of personalisation should necessitate reduced passenger participation to mitigate the cognitive burden often associated with complex PIS. However, the authors acknowledge that alternative conceptualisations of personalisation levels could arise from considering other salient challenges, such as user control or demand management. For example, adopting a developer's perspective could offer valuable insights into identifying new core functionalities for PIS that automate decisions typically made by system developers. Future research could explore various perspectives on personalisation levels, including perspectives focusing on the accuracy or effectiveness of personalised systems. However, perspectives that are not user-oriented may conflict with user requirements, particularly regarding the level of control users wish to maintain over the personalisation.

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Appendix

Table A1. Review of studies discussing personalisation in passenger information systems.

Publication	Location	Target	Description of personalisation	Functionalities of PIS	Object of Personalisation	Initiator	Types of Input Data	Source of Input Data	Trigger for Personalisation
Titov et al. (2020)	Karlsruhe, Germany	Public transport passengers	By linking the passenger's mobile device to the public display of the PIS, personal data is shared, allowing the PIS to tailor travel information on the public display.	Process situation of trip, Process status of PT network, Generate user profile, Detect and locate user, Assign pseudonym to user	User interface	User-initiated	User preference, Attributes of travel situation	User input	Connection between user's smartphone and smart window
Herzog et al. (2017)	Munich, Germany	Public transport commuters	The PIS enhances collaborative travel preferences of communities with pre-defined user preferences in the form of filters to provide a personalised ranking of route recommendations	Generate user profiles from survey data, Process collaborative preferences, Generate route recommendations, Ask for feedback	Route recommendation	User-initiated	User preference, Attributes of route, popularity of route	Google maps API user input, historical database	Interaction with application
Keller and Schlegel (2019)	Karlsruhe, Germany	Public transport passengers	By tracking passengers and their devices, the PIS adjusts whether relevant travel info appears on a public display or their mobile device	Detect and locate user, Match available modalities and devices with user's preferences	User interface	System-initiated	Location of passenger	Mobile device(s) of passenger	Connection between user's smartphone and public transport vehicle
Brossard et al.(2011)	Lille, France	Public transport passenger in a certain area	When locating the passenger, personalised information regarding points of interest can be provided to the passenger	Detect and locate user, Change content based on users' location	Travel information	System-initiated	Location of passenger	Mobile device of passenger	Location of user

(*Continued*)

Table A1. Continued.

Publication	Location	Target	Description of personalisation	Functionalities of PIS	Object of Personalisation	Initiator	Types of Input Data	Source of Input Data	Trigger for Personalisation
Bajaj et al. (2015)	Delhi, India, and Paris, France	Metro passenger in urban areas	PIS that gathers sensory information and user-generated content to deliver personalised transport updates as per passenger's mobility preferences	Model convenience level, Model user preferences, Generate route recommendations	Route recommendations	User-initiated	Location of passenger, user preference	Survey, mobile phone	User request
Namoun et al. (2021)	Nottingham, U.K., and Sofia, Bulgaria	Public transport commuters	PIS suggest eco-friendly routes after receiving traffic flow forecasts from a real-time traffic prediction tool	Process traffic conditions, Generate route recommendations	Route recommendation	System-initiated	Traffic flows	Road sensors	Emission levels in environment
Chowdhury and Giacaman (2015)	Auckland, New Zealand	Public transport passengers	By selecting a trip purpose from a predefined list, the PIS personalises system functions	Adjust planning features of the application to user's travel situation, Process status of the PT network, Generate route recommendations	User interface	User-initiated	Trip purpose, Location of passenger, GTFS real-time	Google directions, smartphone	User request
Al-Rahamneh et al. (2021)	Pamplona, Spain	Travelers in multi-modal urban networks	After users set preferences, the PIS personalises routes using environmental sensory data from the environment matching the preferences	Generate user profiles, Generate route recommendations, Process status of pt network, Update user on changes in route recommendations	Route recommendation	User-initiated	User preference, GTFS real-time	PTO/PTA, survey	Changes in travel condition
Campigotto et al. (2017)	Vienna, Austria	Travelers in multi-modal urban networks	After collecting stated preferences to overcome the cold start problem, the PIS personalises route recommendations using an user profile built from revealed preferences.	Process user profile, Model mass preference classes, Update user profile based on interactions with the system, Model the weights for utility function, Generate route recommendations	Route recommendations	User-initiated	User preference, Attributes of travel situation, GTFS real-time	Survey, PTO/PTA	User request

Kazhamiakin et al. (2021)	Trentino, Italy	Travelers in multi-modal urban networks	The PIS personalises game challenges through mode recommendations based on the player's travel history	Generate travel patterns of users, Update travel patterns based on interaction with systems, Provide rewards for sustainable travel behaviour, Provide feedback to users on travel behaviour, Generate route recommendations	Route recommendation	System-initiated	Historical travel behaviour	AFC	User request
Li et al. (2023)	Shenzhen, China	Urban Rail passengers	A collective filtering algorithm personalised route recommendations by considering both individual and similar passengers' preferences	Generate user profile from historical travel data, Model collective filtering, Generate route recommendations	Route recommendation	System-initiated	Historical travel behaviour, User preferences	AFC, Station data, Route data	User request
Borodinov and Myasnikov (2020)	Samara, Russia	Public transport passengers	By modelling the user's stop and route preferences, the PIS personalises recommendations for the specified OD pair	Generate user preferences, Process real-time travel information, Generate route recommendations	Route recommendation	System-initiated	Historical travel data, GTFS real-time	PTO/PTA	User request
Panou (2012)	Thessaloniki, Greece	Public transport passengers	With a combination of stated and revealed user preferences, the PIS can personalise the route recommendation	Process user preferences, Process user interaction with system, Generate route recommendations	Route recommendation	User-initiated	User preferences, historical travel data, GTFS real-time	PTO/PTA, survey	User request
Jenelius (2020)	Stockholm, Sweden	Public transport passengers	By analysing the crowding in the vehicles, the PIS is able to provide personalised crowding information	Model predictive user load and crowding levels, Generate route recommendations	Travel information	System-initiated	Historical travel data	PTO/PTA	User request
Wins et al. (2024)	Germany	Travelers in multi-modal urban networks	With stated user preferences for activities and mobility, the PIS personalises travel itineraries	Process user preferences, Process travel situation, Process status of environment, Generate route recommendations	Travel itinerary	User-initiated	User preferences, attributes of travel situation, weather conditions	PTO/PTA, user input, breezometer	User request

(*Continued*)

Table A1. Continued.

Publication	Location	Target	Description of personalisation	Functionalities of PIS	Object of Personalisation	Initiator	Types of Input Data	Source of Input Data	Trigger for Personalisation
Kühn et al. (2019)	Germany	Public transport passengers	Connecting a mobile device allows the PIS to show personalised info on a public display	Process user preferences, Detect and locate user, Process status of pt network, Highlight relevant information on display channel	User interface	User-initiated	location of passenger, trip purpose, social demographics, time	PTO/PTA, personal settings on mobile phone	Connection between public display and mobile device of user
Naumann and Wolf (2011)	Magdeburg, Germany	Public transport passengers	After specifying the planned journeys of the passenger, the PIS personalises re-planning alerts if deviations occur	Process status of pt network, Recalculate route recommendation	Route recommendation + notifications	Route: user-initiated, Notification: system-initiated	User travel constrains, GTFS real-time	PTA/PTO, user input	Change in travel conditions
Bouhana et al.(2013)	Carthage-El Manar, Tunisia	Travelers in multi-modal urban networks	By storing past interaction with the PIS, the PIS can provide personalised predictions on future travel behaviour	Process user preferences, Process travel situation, Store interactions with system, Update user profile based on interactions with system, Generate route recommendations	Travel itinerary	System-initiated	Historical interactions with system, attributes of travel situation, user preferences	User input, application system	User request
Ceder and Jiang (2019)	Copenhagen, Denmark	Public transport passengers	Stated preferences are weighted across time of day and day of week to provide personalised route recommendations	Process user preferences, Process status of pt network, Detect and locate user, Process user feedback, Generate route recommendations	Route recommendation	User-initiated	User preferences, GTFS real-time	User input, PTO/PTA	User request
Lathia et al. (2013)	London, U.K.	Public transport passengers	The PIS analysis collective historical travel data to personalise the travel time estimations of route recommendations	Cluster user travel patterns, Process travel situation, Generate route recommendations	Route recommendations	System-initiated	Historical travel data	PTO/PTA	System inference

Aguiar et al. (2012)	Portugal	Public transport passengers	The PIS uses RFID based e-ticketing to locate the passenger and provide personalised navigation assistance	Detect and locate user with ticketing activation, Process status of pt network, Generate navigation assistance	Navigation	System-initiated	Location of passenger, Attributes of travel situation	PTO/PTA	Validation of ticket
Barbeau et al. (2010)	Tampa, U.S.A.	Cognitive challenged public transport passengers	The PIS allows passengers to start a predefined trip and receive personalised navigation assistance for this trip	Process trip situation, Process user situation, Process status of pt network, Detect and locate the user, Generate alerts in case of deviation from path	Navigation	User-initiated	Attributes of travel situation, environmental characteristics User input, GPS, real-time travel information	User input, GPS, real-time travel information	User request
Földes and Csiszar(2015)	Budapest, Hungary	Public transport passengers	The PIS provides personalised route recommendations based on physical properties of the routes and stated user preferences	Process trip situation, Process user preferences, Generate route recommendation	Route recommendation	User-initiated	User preferences, GTFS real-time	User input, PTO/PTA	User request
Esztergar-Kiss et al. (2021)	Budapest, Hungary	Commuters in multi-modal urban networks	The PIS provides personalised route recommendations based on utility functions with individual preferences	Process user preferences, Process status of pt network, Collect feedback from user, Process user feedback, Generate route recommendations	Route recommendation	User-initiated	User preferences, GTFS real-time	User input, PTO/PTA	User request
Lathia et al. (2012)	Napoli, Italy	Public transport passengers	By deriving user preferences from historical travel behaviour, the PIS can send personalised travel alerts	Process travel patterns, Generate user preferences, Generate route recommendations	Travel information	System-initiated	Location, historical travel data	PTO/PTA	Change in travel conditions
Meloni et al. (2013)	Cagliari, Italy	Travelers in multi-modal urban networks	By tracking the passenger's activity patterns, the PIS can provide personalised travel plan	Process historical travel data, Generate route recommendations	Travel information	System-initiated	Historical travel behaviour	PTO/PTA	System inference

(*Continued*)

Table A1. Continued.

Publication	Location	Target	Description of personalisation	Functionalities of PIS	Object of Personalisation	Initiator	Types of Input Data	Source of Input Data	Trigger for Personalisation
Yatskiv et al. (2023)	Riga, Latvia	Public transport passengers	The PIS lets users rank route attributes for personalised recommendations	Process status of pt network, Process user preferences, Generate route recommendations	Route recommendations	User-initiated	User preferences, real-time travel information	User input, PTO/PTA	User request
Nakamura et al.(2016)	Fukuoka, Japan	Public transport passengers	By monitoring user interactions in both travel behaviour and HCI, the PIS proactively delivers personalised route recommendations	Record user interactions with system, Process historical travel behaviour, Generate route recommendations	Route recommendations	System-initiated	historical travel data	Internal database	System inference
Song et al. (2018)	Boston, U.S.A.	Travelers in multi-modal urban networks	The PIS provides personalised route recommendations with incentives for energy reduction based on revealed user preferences	Process status of pt network, Process user preferences, Generate route recommendations	Route recommendations	system-initiated	GTFS real-time, user preferences, network structure	PTO/PTA, user input	User request
Giubergia et al. (2024)	Cagliari, Italy	Travelers in multi-modal urban networks	By analysing the travel patterns of the passenger, the PIS can provide personalised travel plans to change the travel habits	Process trip situation, Process environmental data, Generate route recommendations	Route recommendations	System-initiated	historical travel behaviour	PTO/PTA	System inference
Sottile et al. (2021)	Rome, Italy	Travelers in multi-modal urban networks	By tracking the passenger's activity patterns, the PIS can provide personalised travel plan	Record travel behaviour of user, Process historical travel behaviour, Generate route recommendations	Travel information + Route recommendations	System-initiated	Historical travel behaviour, Attributes of travel situation	Smartphone	Historical travel behaviour
Gault et al. (2019)	Aberdeen, Scotland	Public transport passengers	The PIS tracks travel patterns and ecosystem status to send timely updates on frequent routes	Process trip situation, Process user preferences, Process status of ecosystem, Generate travel information	Travel information	System-initiated	Historical travel behaviour, Attributes of travel situation, social media content	User input, twitter	System inference

Nunes et al. (2011)	Portugal	Public transport passengers	The PIS tracks passengers to offer personalised travel updates using service feedback from en-route passengers	Process status of pt network, Generate user profiles, Detect and locate user, Update user profiles over time, Generate travel information	Travel information	System-initiated	GTFS real-time, location of passenger, Attributes of travel situation	PTO/PTA, GPS, user input, API	System inference
Solar and Marques (2012)	Spain	Travelers in multi-modal urban networks	When passengers register a trip, the PIS can send personalised alerts once travel begins	Process status of pt network, Process trip situation, Generate user profile, Generate travel alerts	Travel information	User-initiated	GTFS real-time, Attributes of travel situation, environmental data	PTO/PTA, sensors	Passenger starting trip
Qoradi et al. (2021)	Riyadh, Saudi Arabia	Student commuters to campus	After pick-up registration, the PIS alerts passengers when the bus is 5 min away	Process pick-up location, Process user preferences, Generate travel alerts	Travel information + timing of provision	System-initiated	Attributes of travel situation, user preferences, home-location user	PTO/PTA, geofencing	Bus entering geofence
Anagnostopoulou et al. (2017)	U.K., Austria and Slovenia	Travelers in multi-modal urban networks	By stating the user preferences, the PIS can provide personalised route recommendations	Process user preferences, Generate route recommendations	Route recommendations + persuasion message	User-initiated	User preferences, historical travel behaviour, Attributes of travel situation	User input	User request
Handte et al. (2016)	Madrid, Spain	Bus passengers	When connected to the vehicle, the PIS provides personalised micro-navigation to the passenger	Detect and locate user, Connect vehicle with mobile device of user, Process trip situation, Generate navigation assistance, Generate crowding levels in vehicle	Travel information + navigation	User-initiated	Attributes of travel situation, location of user, location other users	User input, PTO/PTA	Connection between vehicle and user
Wang et al. (2024)	Beijing, China	Urban rail passengers	By combining stated preferences with AFC data, the PIS is able to provide personalised route recommendations	Process historical travel behaviour, Process user preferences, Process status of the pt network, Generate route recommendations	Route recommendations	User-initiated	Historical travel behaviour, user preferences, GTFS real-time	PTO/PTA, user input	User request

(*Continued*)

Table A1. Continued.

Publication	Location	Target	Description of personalisation	Functionalities of PIS	Object of Personalisation	Initiator	Types of Input Data	Source of Input Data	Trigger for Personalisation
Sattar et al. (2024)	London, U.K.	Public transport passengers	Scanning an RFID tag lets the PIS inform others of passengers' special needs	Process user preferences, Process crowd information, Generate travel information	Travel information	User-initiated	Location of passenger, user preferences	RFID tags, Tap-in with card to share personal information	Tap-in with card
Ferreira and Dias (2023)	Porto, Portugal	Travelers in multi-modal urban networks	By deriving user preferences from historical travel behaviour, the PIS can send personalised route recommendations	Process historical travel behaviour, Process user preferences, Process status of the pt network, Generate route recommendations	Route recommendation	System-initiated	Location of passenger, historical travel behaviour, time of day	PTO/PTA	tap in with card