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USE OF AN AI-BASED DIGITAL PREDICTION MODEL FOR THE EVALUATION OF URBAN INFRASTRUCTURE IN TERMS OF ACCESSIBILITY AND EFFICIENT URBAN MOVEMENT FOR PEOPLE WITH DISABILITIES

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Abstract

Purpose: Ensuring accessible urban infrastructure remains a challenge to inclusive societies and equal participation of people with disabilities in economic, cultural & social life and is thus a stunting factor in economic development. This paper proposes using an Artificial Intelligence-based model for evaluating accessibility in urban infrastructure towards identifying & predicting problematic areas in the existing or future built environment. The objective is to describe a reliable and extensible model capable of detecting mobility-problematic areas, evaluating the quality of urban infrastructure, proposing alternative routes and creating the base of a holistic detection and evaluation digital tool for better urban planning and efficient application of European Social Policies.

Methodology: The research identifies obstacle and difficulty components useful within a Digital AI system via structured interviews performed with members of 2 key organizations in social development and inclusion in Eastern Macedonia and Thrace, Greece.

Findings: The set of obstacles and difficulties is aggregated in a vector of solvable difficulties suitable for an AI system. Additionally, we propose methodologies for collecting and comparing data from predefined pilot routes between people with disabilities and the general population to build an initial training dataset for a continuous decision-making and evaluation AI system.

Originality: Research originality is derived from combining Artificial Intelligence with the sector of computational evaluation of material infrastructure, as perceived by humans with disabilities, and as a tool of increased economic activity. It additionally defines key obstacles perceived by PwDs that are sufficiently measurable and subsequently solvable by AI.

Keywords: Social Inclusion; Artificial Intelligence; Accessibility; Urban Planning; Prediction Models; AI-based Methods;

JEL codes: C63; I31; R42;

1. Introduction

Artificial Intelligence (AI) has brought forth a revolution in computing during recent years. AI, along with its sibling technologies (Deep Learning, Internet of Things - IoT), has been applied to a broad range of sectors in business, industry & society as part of the shift towards Industry 5.0 (European Commission, 2022) and the 4th Industrial Revolution. As the potential of AI unfolds, it's increasingly seen as a powerful force for driving positive social change and economic growth. This effort of using Artificial Intelligence for the benefit of social cohesion in addition to profit is further highlighted in Europe's Coordinated Plan for AI (European Commission, 2021), as well as the European AI Strategy (European Commission, 2018), where development strategies for human-first Artificial Intelligence (that is, AI that works for the benefit of society) are proposed. Similar initiatives have been observed around the world, and particularly interesting is the case of Japan and the Society 5.0 strategy of the Japanese Cabinet Office (Council for Science, Technology and Innovation Cabinet Office, Government of Japan, 2021), where AI is featured as a necessary proponent of societal change, assisting humans in the burdensome task of processing larger amounts of data & information. With all the above in mind, we observe that European society has arrived at a breakthrough point: where development teams in charge of innovative projects have access to powerful AI technology that can boost both their business value and improve social cohesion by solving social issues in parallel.

Such a social issue is the general accessibility of the built urban environment to people with disabilities, leading to decreased participation of PwDs in the labour market and, therefore, stunted economic growth and inefficient application of active European policies on employment and social affairs (which include labour market policies in ensuring equal, unobstructed access to employment). 87 million Europeans possess some sort of disability (1 in 4 people) (European Council, 2022), with over 50% of those people feeling discriminated against and at risk of being socially excluded. Generalized accessibility is a counter to the above: better built environment accessibility (to services, transportation, business sites and nature) leads to better social thriving & quality of life (Forster et al. 2023), and, in turn, a more thriving economic environment. In the scope of this paper, we attempt to assess the usefulness of AI being used for the benefit of people with disabilities (in terms of mobility, access to employment, and the economy in general), and the "if and how" AI can be put to work to measure and evaluate the urban environment, towards a truly feasible solution.

Social issues arising from lack of accessibility to people with disabilities are rampant in Greece. Indexes and data to evaluate the situation are far and in between. However, the European Semester 2020-2021 country fiche on disability in Greece (European Commission, 2021) (and later European Semesters compounding the issues) identified a widespread disability equality gap across all sectors & studied indicators. In specific, employment rates for disabled people remain some of the lowest across Europe, with disability inequality made further worse due to high levels of long-term unemployment (both in male/female persons & youths). More importantly, disabled people suffer from direct or indirect discrimination at the workplace and continue to encounter inaccessible physical and digital environments. This inequality due to inaccessible physical spaces in the built urban environment is precisely the issue we focus on in this study, and constitutes the main elements of our research hypothesis: how the proposed AI digital system of this paper can help in mitigating the problems of lessened urban accessibility for People with Disability, through continuous measurements of the built environment and by bringing into light previously unknown (i.e. unmeasured and undocumented) problematic areas within it.

To bring the matter closer to home and to raise locally relevant knowledge on disabled-person physical accessibility, we consulted and cooperated with two (2) local disability-relevant groups and organizations: namely, the Limited Liability Social Cooperative of Kavala (Kavala's LLSC; KOISPE), employing a large number of disabled individuals as well as actively participating in (and, as an institution, having a statutory purpose of) serving common welfare, local development and social cohesion, and the Prefectural Association of People with Disabilities of Kavala, the primary body representing citizens with disabilities in the targeted locality of Kavala.

We conducted focus group interviews with those two bodies, and consolidated the results. In subsequent parts of the study, we present a feasible AI prototype that can use the problem's specifications as *input* and produce *solutions*. Finally, the study concludes with discussion & remarks on the effectiveness of the solution, possible challenging sub-problems and areas of improvement, and a discussion on the still-developing issues of ethics & AI development.

2. Literature Review

Early visions of how AI can assist in the recovery and/or daily activities of people with disabilities (temporary or permanent) exist throughout the scientific literature. Teng & Ren (Teng & Ren, 2021) identify the shift of AI development from *computational* intelligence to *perceptual* intelligence (able to use *perceived* input, not only prepared digital data), as well as its more widespread availability and usability, and highlight its potential towards building barrier-free urban environments that support self-recovery and promote deinstitutionalization as outlined per Anthony (Anthony, 1993). However, Teng & Ren (Teng & Ren, 2021) propose AI only as a component of constructing medical data aggregator platforms, humanoid robots, or space-regulating systems (smart homes) and do not venture into the realm of PwD urban mobility assisted by AI. Kaneda et al. (2020) successfully devised a deep-learning methodology for evaluating road surfaces based on wheelchair vibrations during movement. Their deep learning model, while only taking into account the acceleration variable ($\boldsymbol{\alpha}$) for the dataset of tested wheelchair routes it was trained on, can predict & classify the harshness of a road surface with 85.3% accuracy and an 89.8% correlation accuracy with human-perceived accuracy (through questionnaires to wheelchair users on the same surface). In the same vein, Iwasawa et al. (2013), stemming from a lack of widely available data on the urban surface categorization of *difficulty*, described an on-the-go processing system for judging road & curb accessibility. Their system, using commonplace sensors found on mobile devices, achieved an 89.6% accuracy rate on surface difficulty detection compared to the in-vivo judgment of a human companion to the wheelchair user. Both previous papers also note that the existence of a more massive dataset on urban infrastructure accessibility & obstacles could feed into better AI solutions on the matter. On a less technical basis, Alashkar et al. (2020) propose that Artificial Intelligence increases human agency and removes barriers preventing millions of disabled people from participating equally in public (social or economic) life, and identifies AI itself as a major transformative force in building ICT systems for social good. Moreover, as a sister technology, AI and IoT were identified by Mochizuki (2019) as facilitators in creating

Social Value, through their usefulness in creating smart cities & generalized citizen-centric, economically sustainable systems.

Regarding physical obstacles and what parts of urban infrastructure pose the greatest challenge to people with disabilities, several attempts to define the issue are recorded in scientific literature. Aidonis et al. (2021) highlight the importance of *accessible* spatial infrastructure (sidewalks & outdoor areas in general, markers, lack of obstructions, properly accessible walking routes, urban transportation interfaces) and building infrastructure (parking spaces, building entrances & elevators, internal accessible routes such as touch paths, lighting) as two major categories when assessing the measure of accessibility. Cooper et al. (2007) identified specific material barriers as the most important physical obstacles: stairs, steps, curbs, doorways, rough/uneven surfaces, and crowded and/or confined spaces. Kutikova et al. (2017), in a qualitative study on people with various levels of disability, identified more common issues such as the height of a sidewalk's curb, or the length that a crossing's green light remains green, and even unexpected factors such as roadworks or construction on their route. The importance of expected & unexpected obstacles was that all participants in Kutikova's study required a separate layer of *planning & preparation* before going out into the urban environment.

While this paper discusses artificial intelligence as its major proponent in calculating data to solve accessibility issues and map suitable routes, other assistive ICT solutions that do not necessarily integrate AI have been proposed. Kozievitch et al. (2016) propose a data-aggregation system that produces suitable routes for wheelchair users by analyzing different map layers & available Open Data from different services. Goldberg & Zhang (2018) investigate a cyber-physical framework that would connect people with disabilities to their surroundings via smart sensors in the urban environment, allowing for elevated decision-making. Devigne et al. (2019) even go as far as to design a digital co-pilot for the wheelchair: a smart agent that shares control with the user and assists in situations of difficult terrain traversal or risky wheelchair maneuvers.

About the economic repercussions of accessibility & inclusivity, Bilevičienė et al (2011) find a definitive link between enhanced active labour policies and increased participation of the disabled (and generally the disadvantaged) in employment, leading to a more competitive economy and more opportunities for SMEs. Moreover, Misiūnas et al. (2009) view economic & social development as synchronous, meaning economic and societal growth are interlinked and to be pursued in parallel towards achieving truly sustainable development models.

In a broader macroeconomic scope, Bilevičienė (2014) suggests more factors, other than simply Gross Domestic Product (GDP), in evaluating a country's economic growth - and these factors include active labor market policies and rising employment levels as indicators: Bilevičienė finds positive correlations between applying active labor market policy measures towards minimizing unemployment and increased participation of citizens in economic, cultural and social life, leading to economic tonicity and improved quality of life. Moreover, the authors tie the disadvantaged access of the disabled to social and economic resources into a two-prong issue of *social cohesion* as analyzed by Melnikas (2013): cohesion between various social groups or social layers within a national context is impaired due to personal wealth & wellbeing disparities between the disabled and the not disabled, and cohesion between various activities, between the sectors of social, economic, political, cultural, scientific and technological development, as well as various spheres of social activities or business is also hindered due to the unequal access of the disabled to socio-economic life. In turn, social cohesion, even though a precondition, when impaired, remains a thorn in the process towards the effective creation of a knowledge-based society and knowledge economy and the intellectualization of modern society as a whole.

Finally, social entrepreneurship is a viable vehicle of bringing forward innovation on this subject of AI-assisted PwD mobility. Kostas et al. (2018), Kostas (2022) & Tsoukalidis et al. (2022) discuss that social enterprises, as avenues of social entrepreneurship, are engaged in regional development schemes to create social value, promote collective work & cultivate innovative practices & “fresh ideas” while addressing societal issues, in parallel to economic activity & value creation as businesses.

3. Research Methodology

Our research approach entails the use of focus group interviews (which, as per Krueger (1988), are well-organized team conversations that intend to deduce perceptions on a specific issue under investigation within an eloquent and unobstructed environment) to address, verify & quantify the problems of urban mobility for people with disabilities on the local basis of Kavala, Greece, then funnel our research findings into creating the pre-design of an AI system that could solve these issues on multiple levels (*pre-* and *post-* assistance). We conducted *horizontal* interviews, that is, interviews that focused more on discussions among participants than individual discussions between the research team and each participant. This method reduces the control of the research team over research results and augments the significance of the participants’ own responses (Frey & Fontana, 1991). The vibrancy & exuberance afforded to our discussions by utilizing focus groups, as also noted by Kitzinger (1994), is another advocating factor for us choosing this method.

To select suitable (as in, relevant) stakeholders as participants in our focus groups, we keep in mind that the work of Social enterprises (such as the aforementioned Kavala’s LLSC in previous sections), fosters social advancement for *all* (fair opportunities) and forges strong social bonds amongst the various socioeconomic groups active in the locality, to build a vibrant, dynamic and above all, sustainable social economy. As such, Social Enterprises balancing in the “middle” of business innovation & economic development, addressing social issues, and social value addition are an appropriate means of nurturing the efforts of creating the solutions described in this paper.

Regarding our choice of relevant organizations, the LLSC of Kavala, having commenced operations in 2011, is the first institutionalized entity in the sector of Social

Economy, especially in the social entrepreneurship field, in Eastern Macedonia & Thrace, Greece. Kavala's LLSC designs & implements social economy programs granting significant advantages to beneficiaries in terms of employability and psychological support, executes development projects on a local and national stage, functions as a personnel recruiter and caters for diverse service fields, by facilitating the provision of upgraded employment opportunities, social services, welfare, healthcare, environmental & administrational, financial, educational or other services of public interest (Kostas, 2022). Additionally, the Prefectural Association of People with Disabilities of Kavala, founded in 2001 and restructured in 2010, is the primary body of representation of disabled individuals in the municipality of Kavala. As indicated by its statute, the association's purpose is to organize, brief, and support PwDs. Its elected governing board is characterized for its diversity, as its members represent major categories of disability, (movement disabilities, blindness, deafness, multiple sclerosis, insulin-related disease, kidney diseases, parents of children with disability and receivers of psychological support services). The association's purpose also includes the provision of visibility & dissemination on issues of disability, related to the persons themselves or their families, granting them a meaningful voice during decision making on a local or national level.

We conducted two (2) focus group interviews: one at Kavala's KOISPE (LLSC), with employees, beneficiaries and executives of the organization belonging to various disability groups or not disabled but knowledgeable on the subject of urban mobility for the disabled, and one at the Prefectural Association of People with Disabilities of Kavala, with its members fully belonging to groups with disabilities. As a first step and from both those organizations, official emails were sent out to their respective members, informing them on the purpose of our research and openly calling any and all interested persons to partake. Prior to the actual interviews, telephone, e-mail and in-person communications were performed with interested participants that have come forth from the two organizations, to coordinate the date & time of the meetings. In these prior communications, both organizations (Kavala's KOISPE & the Prefectural Association of PwD of Kavala), as per our own organization's instructions (Bluechain Research Cooperative) to suggest candidates for the interview that represented distinct worlds of disability in an effort to better encapsulate the problem in our research hypothesis, suggested participants that were interested, available, and belonged to different classes of disability. The final participants of the survey were again informed about the purpose of the research, its objectives, the estimated duration of the interview and its structure. A brief dissemination of the prepared questionnaire took place in each of the two organizations to help participants better understand the questions and allow them to prepare beforehand should they require clarification. All survey participants from both organizations agreed to participate in the interviews.

The first focus group survey was conducted on 08/03/2023 in the premises of Kavala's KOISPE and lasted three (3) hours. Eight (8) participants joined in (5 men and 3 women):

Table 1: Participants in the first focus group

Participant ID	Disability or Knowledge Group
P1	Wheelchair user
P2	Wheelchair user
P3	Wheelchair user
P4	Blindness and vision impairment
P5	Blindness and vision impairment
P6	Policy-making on Accessible Urban Environments
P7	Policy-making on Accessible Urban Environments
P8	Policy-making on Integration of Disabled Persons

The second focus group survey was conducted on 14/03/2023 in the premises of the Municipal Association of Kavala's PwD, and it, too, also had a duration of three (3) hours. Five (5) participants joined in (4 men and 1 woman):

Table 2: Participants in the second focus group

Participant ID	Disability or Knowledge Group
P9	Wheelchair user
P10	Wheelchair user
P11	Mobility Impairment, non-wheelchair user
P12	Blindness and vision impairment
P13	Blindness and vision impairment

The gathered sample of participants strongly represented the targeted disability groups in our research hypothesis, and could produce strong & reliable evaluation results towards both our hypothesis and measurements of the problems in urban mobility, and our later-discussed technical solution.

The questionnaire consisted of eight (8) thematic questions designed to foster open discussion in areas of common interest to the participants so as to generate additional feedback for our research. Participants were encouraged to answer the questions with a sense of freedom, based on their own experiences and opinions without strict guidance by our interviewers., As a result, more leading to robust qualitative findings were extracted through this liberal interview process. Our team designed the thematic questions themselves to progress the theme iteratively: to begin with the interviewee's general assessment of PwD mobility as they experience it themselves (or through their family & peers), then move towards specific problems they identify in their environment, then widening the scope to their comparative experiences in other locality, and finally allow interviewees to talk about specific factors that help or pose particular difficulty in their day-to-day experiences. The questions were the following:

Q1. Problems the interviewee has experienced with urban mobility in their local urban environment.

Q2. Specific problems in the realm of wheelchair mobility or visually-impaired mobility the interviewee has experienced or observed/deduced through their co-citizens.

Q3. Comparison of the interviewee's local mobility ecosystem & problems experienced/observed versus other localities he/she has visited or studied.

Q4. Identification of specific elements in urban construction that pose the most challenges for wheelchair users, visually-impaired persons or generally mobility-impaired persons.

Q5. Current technical aids or technological tools that the interviewee uses to assist him/her in everyday mobility or has observed or been recommended through their peers & co-citizens

Q6. General time, effort & preparation are required for a simple walk outside for a person with disabilities.

Q7. Difficulties observed during participation in public life (social, economic) for a person with disabilities.

Q8. Views on the interviewee's self-agency and stance on asking others for help (e.g., passers-by) if and when required during a simple walk outside.

The conversations during both focus group interviews were lively and highly interactive. They revealed deep perspectives on the issues of urban mobility for persons with motor disabilities, especially wheelchair users and the difficulties they face in their participation in everyday life. Our interviewers recorded in writing all answers to the questions by each participant. Additionally, they kept footnotes on subjects not presented in the questions but mentioned or discussed by the interviewees themselves.

All previous answers were transcribed digitally using simple matrices in spreadsheet software *(Google Sheets)*. Subsequently, answers were collated and categorized into different columns, to find common and quantifiable denominators in the answers received by interviewees. The category columns are:

C1. Type of difficulty: *Material* (physical barriers) or *Immaterial* (psychological barriers, time spent on a route).

C2. Time nature of difficulty: *Static* (physical barriers that are a persistent part of the urban environment) or *Dynamic* (barriers that aren't persistent to the environment, such as incorrectly parked cars or roadworks, or vary depending on participant/user).

C3. Relevance of difficulties to different kinds of PwD movement: *Difficulty for Wheelchair Users (P.Wh)*, *Difficulty for Vision Impaired Persons (P.VI)*, *Difficulty for non-disabled, healthy persons (P.NonD)*.

C4. The severity of difficulties: Minor (requires minor preparation and/or minor effort by the PwD to overcome), Moderate (requires strong effort by the PwD to overcome and might pose a complete barrier to less physically adept PwDs), and *Severe* (poses a completely impassable barrier for a PwD).

After categorization, the results are put together as components of a **horizontal initial difficulty vector $\mathbf{V_D}$**: a simple vector organized horizontally (per line of the matrix), with each component being a vertical sub-vector containing the categorization values of the obstacle as per each category. The vector form assists in fully and completely encapsulating the useful information gained through focus groups before attempting any calculation in an AI system. Afterward, we sanitized the resulting vector V_D by removing uncontrollable components. We used the remaining data as a starting point in proposing a **solvable difficulty vector $\mathbf{V_{S(D)}}$ that contains only those components sufficiently measurable and able to be calculated towards a holistic system, employing AI in its various methods** to measure barriers & augment urban PwD mobility.

4. Results

4.1. Focus Group interview results

All, bar none, of the survey participants, while answering *Q1*, had experienced great difficulties while getting around the urban environment of Kavala, Greece, or observed difficulties in their peers with a disability, and some often employed the help of a close person for assistance. This was attributed not only to the particularly hostile terrain of the city (built on a steep incline) but also to the lack of proper accessibility infrastructure or maintenance of existing accessibility features of the built environment. Survey participants had various experiences to share in the interview, relating to them directly. Even simple tasks such as going to the markets in the city center, going to their place of employment, visiting a Public Service, joining a cultural event, taking a bus or going for a simple walk required either meticulous planning of the route beforehand, almost always extra time beforehand so that the PwD could overcome movement obstacles, or was altogether impossible if the destination was in a difficult to access location (such as the events & venues at Kavala's Panagia district - the city's "Old Town").

During the answering of Q2, specific problematic areas in the urban environment were identified by interviewees. Participants noted the bad state of maintenance in the city's various accessibility systems, such as tactile blocks for the visually impaired, acoustic signal makers for zebra crossings, lack of sufficient width or proper inclination of ramps in Public Service buildings, and non-functional lifting platforms in Public Transit vehicles (specifically, buses). Interviewees also discussed the general state of disrepair in pedestrian curbs and crossings of the city, posing a major obstacle for people with most kinds of motor or visual disability, as well as their narrow width, steep inclines or lack of on/off ramps at their ends, and the improper, out of planning existence of trees or power poles in their course. Of particular mention to most of the interviewees was the chaotic parking of cars on disabled parking spots or on-ramps to pavements, leading to the inability of PwDs to continue on their route - participants noted that this is due to both the lack of law enforcement by authorities. The widespread disregard of PwDs by members of the typical population is further made worse by the difficulties of PwD participation in public life, feeding into the negative loop of *PwD invisibility* in local society.

Upon answering Q3, all participants proposed that the problem of inefficient accessibility is widespread across Greece. Still, in their answers, the locality (Kavala) was dominant because of their heightened familiarity with the city - most lived here or in neighboring villages. In any case, the problem of ineffective urban infrastructure elements, be it due to mistakes in their construction or bad maintenance, was observed generally. Other, bigger cities like the closest metropolis (Thessaloniki) or the capital itself (Athens), even presented extra challenges that aren't always present in Kavala, such as overcrowding in bus stops or pavements in general, and the complete lack of pavements in some areas, forcing wheelchairs user to use the street and move dangerously close to moving cars. Some participants noted the more frequent existence of roadworks (be it related to power, communications, or plumbing), as observed through the communications they maintain with peers in the vicinity of those cities. The difficulties were common in accessing ancient or historical places, with the hill of Lycabettus being compared in terms of difficult accessibility to the old town of Kavala. Participants, instead, noted European cities as a positive example, with more or less all-encompassing accessible urban elements, and much less experienced difficulty in getting around: European capitals such as Sofia, Berlin, Amsterdam, Rome, and Madrid, in which participants had visited, were much friendlier to PwD mobility, according to interviewees, and had common elements of being built around human movement, not cars, which helped in that regard.

Question 4 allowed interviewees to propose specific elements of urban infrastructure that they deemed the most difficult to traverse for PwD. Most participants noted curb width, height, inclination, and surface evenness as important factors in ease of wheelchair movement. Nearly all participants (11/13) mentioned the existence and the width of on-off ramps at the end of pavements and before pedestrian crossings. Some participants also mentioned the existence of cafe/restaurant seating on top of pavements, a phenomenon familiar in Greece as the Municipality itself rents out space for businesses to place seating on, as an obstacle factor in case the tables and seats are too wide (illegally) spread, leaving little room for passage. Most participants also made mention of irregularly parked cars (on non-designated places or on the pavement, or on-off ramps themselves) as a difficulty factor. Lastly, some participants presented time (or time spent en route) as a factor of weariness - the obstacles observed by the PwD take time to negotiate, and this lengthens the route to the point of *weariness*, leading to the individual either deciding to halt the route and return home, or refrain from even attempting the route in the future. These same participants also talked in length about the blow in social participation brought upon the time factor - individuals may cancel appointments or social outings and are psychologically prevented from joining social or economic events due to time spent traveling, leading to more PwD invisibility in local society.

During the Q5 answering, it was found that nearly none of the participants (1/13) used any technical aid to assist them with urban mobility. As noted, no participant had any knowledge of "a digital map equivalent for PwDs", such as Google Maps or Apple Maps, that considers material difficulties in the urban environment. One visually-impaired participant had read about an audio proximity sensor mounted on their cane that could help with detecting incoming obstacles in his everyday outings but did not use it and only planned on researching it more in the future.

In Q6, all participants mentioned that a simple route or walk outside for a person with a disability required magnitudes more time than that of a member of the typical population - even 5 or more times as much. Participants discussed that a 10-minute walk could easily be translated into 45 minutes for a person with a disability, especially a wheelchair user. Most participants (10/13) mentioned, at this point, the extra time required for preparation before the route, often *hours* spent researching the accessibility of the destination building and of the roads in between. Participants often used local or national-level forums and online communities to discuss similar experiences by other PwDs when making similar routes or made telephone calls between them for information. Of particular interest to some participants was the creation of an "online database of accessible places", be it urban or natural/recreational destinations, that does not exist but could help them evaluate whether a place is accessible for them or not.

In Q7, all interviewees agreed that participation in public life for PwDs is asymmetrically difficult. Regarding economic life, most interviewees either admitted or answered through observation of their peers that most PwDs (especially wheelchair users, as noticed by the answers) are unemployed - that is, they do not participate in the economic development of their locality, relying instead on social welfare. Regarding social life, social outings for PwDs (especially wheelchair users and the visually impaired) are scarce, as the built urban environment is either exhausting to travel, leading to more fatigue and an *artificial shortening* of the duration of their outings, or outright barring - preventing them from going out completely, due to fear of being stuck, fear of injuring themselves or fear of inadequate preparation for the obstacles that will surely be met. Participants agreed upon that PwDs often choose the site of their home for social endeavors, as it's a much safer and more accessible place compared to the outside world. Some interviewees made a particular note on the fear they experience of new places - that is, PwDs, especially those with mobility disabilities, have a reduced drive for adventure & discovering new places, as any unpredictability is translated, in their mind, as possible difficulty in their outing. Regarding participation in cultural life, again, the overwhelming majority of interviewees mentioned that it is rare for PwDs to join cultural events or visit culturally-important places spread throughout Kavala and northern Greece in general due to the general inaccessibility of venues, parks, greenery and natural reserves, both of the sites themselves and the roads leading to them.

In Q8, the younger participants tended to answer that they do not ask for passerby help to overcome obstacles, while older participants agreed that sometimes it is required to do so and would accept outsider help more easily during their route. Both age groups of participants, however, agreed that asking for help or receiving help by passers-by was damaging to their sense of agency and empowerment, and they would prefer not to. In this vein, younger participants answered that they actively searched for new assistive technologies that would lead to them not requiring outside help and noted assistive tech as a tool to aid their feeling of self-agency - older participants, while not mentioning that they're actively searching for new tools and technologies to assist them in everyday mobility, also agreed that new tech & digital helpers would be beneficial to their own feelings of self-agency as well. Moreover, some younger participants mentioned that using an assistive technological tool was not, in their mind, the same as asking for help from a human and therefore did not have the same negative effect on their own feeling of self-agency.

The complete dataset matrix was exported to OpenDocument Spreadsheet format (*.ods*) and, for reasons of data posterity, received the following SHA-256 hash:

F82712FEF57E4A52D4CEE1D1759EC295AA0015EB7D08EED1FE3298C32F86F5CB

4.2. Compilation of results towards an AI-based assistive technology

We define the **initial difficulty vector $\mathbf{V}_{\mathbf{D}}$** as the different types of difficulties most encountered by the observed answers of our focus groups, by first categorizing (*casting*) the obstacles identified during focus group answers into categories $\mathbf{C}_{\mathbf{i}}$. Afterwards, we continue the design of our solution only with those obstacles that, after categorization, are deemed controllable and efficiently solvable using AI, through *pre-analysis* and *post-analysis* of PwD routes - meaning, we select those obstacles that are persistent through time in the built environment (for example, O2: lack of ramps unlike O1: parked cars by citizens that can change position throughout the day), or, although immaterial, constitute a more stable measurement of difficulty of a route (for example, O12: time spent in a route instead of the heavily-subjective O13: physical fatigue that can vary from person to person). Those fewer obstacles are thus the components of our ***solvable difficulty vector*** $\mathbf{V}_{\mathbf{S(D)}}$.

Table 3: Identified accessibility obstacles and categorization as per their physical/perceived nature.

Obstacle ID	C1	C2	C3	C4
O1. Parked cars on pavement/route	Material	Dynamic	P.Wh, P.VI, P.NonD	Severe
O2. Lack of curb ramps	Material	Static	P.Wh	Severe
O3. Extreme inclination of curb ramps	Material	Static	P.Wh	Moderate
O4. Blind curb ramps (not leading to pedestrian path)	Material	Static	P.Wh	Moderate

Obstacle ID	C1	C2	C3	C4
O5. Rough/uneven pavement surface	Material	Static	P.Wh, P.VI, P.NonD	Minor
O6. Narrow pavement	Material	Static	P.Wh	Moderate
O7. Extreme inclination of pavement	Material	Static	P.Wh, P.VI, P.NonD	Moderate
O8. Outdoor seating or commercial equipment on pavement	Material	Dynamic	P.Wh, P.VI	Minor
O9. Obstacles on pavement (trees/poles)	Material	Static	P.Wh, P.VI	Severe
O10. Roadworks & construction sites	Material	Dynamic	P.Wh, P.VI	Severe
O11. Time spent preparing for a route	Immaterial	Dynamic	P.Wh, P.VI	Moderate
O12. Time spent en route	Immaterial	Dynamic	P.Wh, P.VI	Moderate
O13. Physical fatigue	Immaterial	Dynamic	P.Wh	Severe

Afterward, we compile the $\mathbf{V}_{S(D)}$ vector by choosing obstacle IDs that are sufficiently persistent in time (Static or Dynamic on a long enough time window to be measured). We can, therefore, be sufficiently recursively solved through AI computation - that is, obstacles that can be identified and categorized either before the route of the user (using the existing dataset) or after the route, by data provided by the user or by automated means of measurement (enriching the existing dataset). Oppositively, we omit from the obstacle set those obstacles O_i that is too dynamic (meaning not persistent enough in time and too dynamic, and thus detrimental to be included in the resulting difficulty vector as their existence would affect calculations without necessarily reflecting reality - e.g., an incorrectly parked car at the time of measurement that moves away 3 hours later), or too subjective in their conditions, or too reliant on a person's own subjective perception (meaning that possible inclusion in the resulting difficulty vector would not be objective to all users of the system - e.g. the physical fatigue of a PwD during a route, primarily reliant on the individual bodily condition of each person with a disability). The omitted obstacles are O1, O11 and O13.

The resulting sufficiently persistent, measurable, and solvable obstacles are:

- O2: Lack of curb ramps,
- O3: Extreme inclination of curb ramps,
- O4: Blind curb ramps,
- O5: Rough/uneven pavement surface,
- O6: Narrow pavement,
- O7: Extreme inclination of pavement,

- O8: Outdoor seating or commercial equipment on pavement,
- O9: Obstacles on the pavement (trees, poles),
- O10: Roadworks & construction sites, and
- O12: Time spent en route.

This leads us to the final definition of our solvable difficulty vector, ready to be used in an AI system aimed at producing PwD mobility evaluation:

$V_{S(D)}$: {O2, O3, O4, O5, O6, O7, O8, O9, O10, O12}

An important note at this point relating to the above vector $\mathbf{V}_{S(D)}$ is that it remains a function of both time and positive three-dimensional space with and as such it would be useful during future implementation to distinctly define a factor Y_i as a multiplicator of each obstacle O_i , that denotes the persistence of that obstacle through time. The factor would be minimal at first detection (for example, $Y_i=0.1$) and maximize during later measurements (for example, $Y_i=1$) , to indicate a long-lasting material obstacle. This aforementioned mechanism also showcases the importance of regular updates of the measurements within the system.

5. Discussion

The results indicate that most of what people with disabilities perceive as difficulties in mobility and accessibility are indeed measurable computationally and additionally able to be sufficiently be processed and evaluated in an AI-based system: Our solvable difficulty vector $\mathbf{V}_{S(D)}$ very closely resembles the initially-recorded difficulty vector $\mathbf{V}_D$, with only two components being omitted. Thus, it is evident that AI can substantially assist in PwD mobility evaluation, when put to work in urban environments that exhibit obstacles of the same types as in $\mathbf{V}_{S(D)}$.

The data used for quantifying components Oi of the solvable difficulty vector VS(D) (apart from trivially measurable components such as time, which is a simple measurement of *seconds*) can be of the following types (Table 4), describing general wheelchair movement in the 3-axis plane (Figure 1).

Table 4: Data types can be used in mobility evaluation per the difficulty vector VS(D) components.

Data	Measurement	Description
Y-AXIS ACCELERATION	(m/s^2)	Acceleration on the axis of forward-backwards wheelchair movement.

Data	Measurement	Description
X-AXIS ACCELERATION	(m/s^2)	Acceleration on the lateral axis of wheelchair movement (left & right).
Z-AXIS ACCELERATION	(m/s^2)	Acceleration on the vertical axis of wheelchair movement (up & down, height).
HEADING	(cardinal direction - deg°)	Direction of wheelchair movement & current facing.
SPEED	(m/s)	Speed (velocity) of wheelchair movement
TILT	Degrees $deg_T°$	Degree of tilt of the wheel-chair's frame on the lateral plane.
GEOLOCATION	Coordinate vector (Latitude, Longitude) & accuracy (meters of deviation) (Geolocation API - W3C Editor's Draft, 2024)	Precise geographic location of the wheelchair, within deviation radius.
ALTITUDE	Meters above the WGS84 ellipsoid (GeolocationCoordinates: altitude property - mdn web docs., 2024)	Altitude position of the wheelchair above sea level.

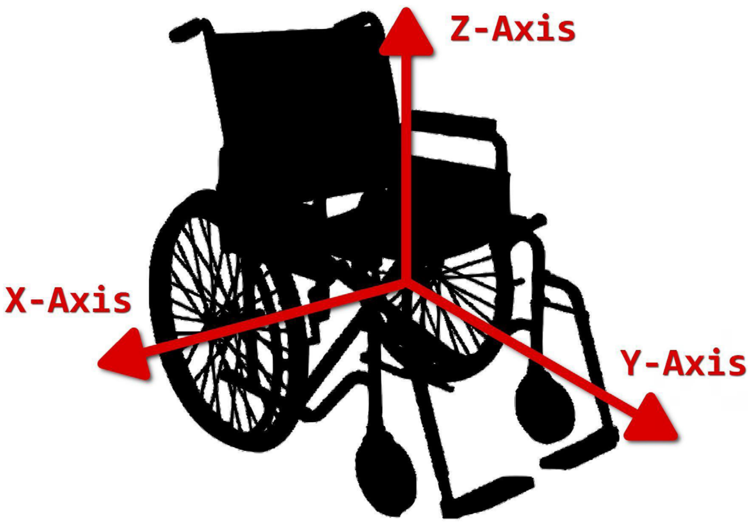

***Fig 1:** Wheelchair movement coordinates on the 3-dimensional plane.*

Suitable sensors are required to record the above data during a wheelchair route. To this, two approaches exist to gather "good" (i.e., accurate) data of such types: using bespoke sensors or repurposing smartphones. While tradeoffs between the two used to be true, recent research indicates that current smartphones gather such data in sufficient quality, easily comparable to specific-purpose sensor devices (Gupta et al., 2015). To gather acceleration data in 3D space, heading, speed, tilt, geolocation & altitude, the phone's onboard accelerometer, gyroscope & GPS module are used.

Using smartphones as sensors allows for versatility in research projects such as ours, leveraging the extreme proliferation of smartphones in everyday life, their continuous advancement, relatively low cost and capacity to perform multiple functions in the same "package", e.g. data gathering & transmission of the data on-the-go towards our aggregation server on the web through the phone's 5G connection, or parallel collection of photographic data in challenging to traverse areas of a route, using the phone's camera.

Moreover, our technical proposition in this paper revolves around striking a novel and valuable middle ground between the previously reviewed work of digital systems built to measure the accessibility of urban environments (using data types such as ones described in Table 4) and in gathering human-provided measurements from participants: that is, to outline a system that leverages AI to pre-calculate the difficulty of a route but also gathers information on-the-go as the route is executed, feeding data back into itself, in a continuous feedback loop, to improve and re-train itself incrementally.

After cataloging observed and solvable (through data inputs and calculation) difficulties, the ontologies and methods required in an AI system designed to solve the problem will be elaborated: that is, the elements required to produce knowledge, through the processing of data inputs, on the status quo of a current built urban environment, evaluate routes, and propose optimal solutions in PwD mobility within that environment.

Before putting AI to work, such a system requires *input*, in the form of a sufficiently large dataset to train it on (that is, a dataset of sufficient length and data quality to produce a system capable of generalization - being able to solve problems hitherto unencountered (Caballero et al., 2006)) - with labeled data, if possible, to enhance feature creation in such a system (Roh et al., 2021). However, training and use of an AI system can be achieved even with lesser datasets, provided steps are taken to improve its accuracy (Motamedi et al., 2021). In this study, the dataset for the proposed AI model is smaller but achieves high targeting and high accuracy to the problem at hand (restricted number of routes to measure, but sampled repeatedly by multiple PwDs, e.g. 20 routes sampled by three different PwDs).

The solving AI model shall entail, at minimum:

A. the initial creation of a dataset based on measured sample routes of PwD in the city of Kavala and
B. the subsequent and frequent enrichment of the dataset based on digital & mechanical sensor input after each route, leading to a gradually better and more accurate core data warehouse on local mobility variables of the built urban environment of Kavala.

The resulting dataset, being at the core of the AI system and iteratively enriched and improved through the AI acting upon it, can be viewed as an accurate digital depiction of **route quality** for the specific city it is tied with (highly-targeted dataset of routes, multiple sampling of routes by separate PwDs to ensure accuracy, resulting in quality training & control sets). Given enough data & data processing cycles, the AI system would be able to detect **hotspots**: zones in the urban environment where a lot of sharp turning and re-routes were identified during measured routes, therefore noting the possible existence of a hard-to-negotiate physical obstacle. This can not only act as an *Early Warning System* for new users seeking to perform that same route but has the potential to act as a Live Classification Tool for urban environment quality & its elements.

Of course, such a system remains dynamic: after a hotspot is detected, subsequent negative measurements (i.e., problems encountered) would result in its gradual de-classification as such. However, an important note to make here, and one easily deducted by the reader, is that classification or de-classification of hotspots *requires* sampling: should a problematic area be improved before or after sampling by the AI system, no change in its categorization can be invoked until after it is measured & sampled again so that the new data can act upon the existing system.

As an example, an initial measured route in the database could look like the following (note: minimal initial measurements were required, apart from the route itself and the duration of it):

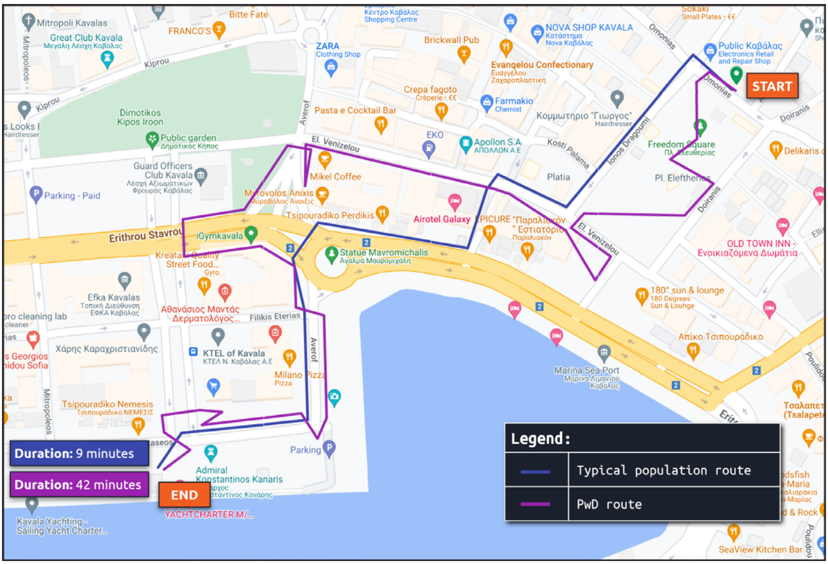

***Fig 2:** A measured route performed by a PwD, compared in time length and maneuvers to the route taken by a member of the typical population, between a pre-set START and END point.*

In contrast, a more advanced version of the same route in the dataset, after multiple iterations of processing and enrichment by extra data-points of different environmental variables (like acceleration data, elevation, continuous geolocation as well as visual data & photos) that would result in the identification of hotspots and those elements that led to the existence of the hotspot, would be akin to this:

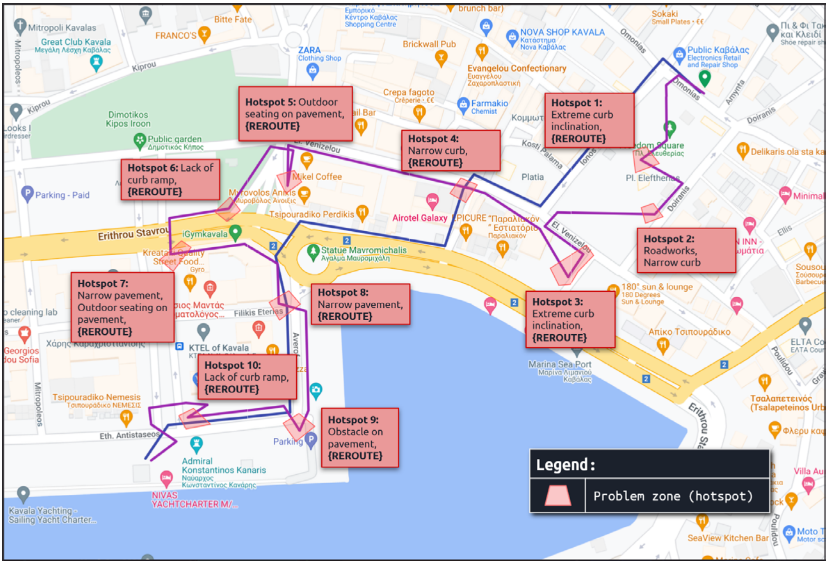

Fig 3: *Hotspot detection in evaluation routes where data was collected, with actions undertaken by the test subject to negotiate encountered obstacles.*

As such, we can use the data collected through the sample routes to let the AI produce evaluations on the accessibility of different urban environment areas. An important distinction would be that such a system should lean more heavily towards permanent obstacles (i.e. permanent elements of the built environment, such as the inclination or surface situation of a pavement along a road) and less towards dynamic elements (i.e. roadworks) as those might become irrelevant as time goes on, but remain part of the AI's iterative calculation cycles.

5.1 Limitations

For reasons of time constraints and cost efficiency, we focused our research and sample groups in the locality of Kavala, Greece. This city is generally built on a significant terrestrial incline and poses distinct and heightened difficulty for PwD mobility. As such, it may be possible that participants in our sample group view some parts of the difficulty vector as more severe than participants from other localities - therefore presenting a risk of participation bias in our research (as per Elston, 2021), in terms of a local sample population of PwDs that possess particular attrition towards specific environmental difficulties. Inversely, it may be possible that PwD participants in other cities of Europe would experience environmental difficulties differently, and their views could differ in what constitutes a severe, moderate, or easy-to-overcome obstacle.

Additionally, although during the creation of our sampling groups, invitations were sent out to the more than one thousand members of the Municipal Association of People with Disabilities of Kavala, only 84 responded. From that pool of 84, our team selected two groups of 20 and 18 as the initial focus groups prior to the second assessment (to better encapsulate the full spectrum of members with movement disabilities, policy, and scientific experts) that led to the final focus groups of 8 and 5 participants. It may be possible that, due to in part the particularly of our target group and the high specificity of our AI solution, our process exhibits signs of selection bias in how we assembled the focus groups and information bias in how we collect data from subjects that already have significant exposure to the problem of urban mobility (Tripepi et al, 2010).

Lastly, specific mention should be made to the issue of data & measurement credibility: in our proposed system, the data recorded via route measurements would be deemed *a-priori* credible and "safe," as a researcher would accompany the person with a disability performing the route. However, in a larger-scale system that possibly operates openly in an urban environment (i.e. used by members of the community not necessarily under direct supervision), specific methods for ensuring data credibility must be defined and enforced, to compensate for scenarios of malicious usage and deliberate poisoning of the automated measuring process and subsequently the AI's process of evaluation - possibly to mark a route as accessible or non-accessible incorrectly.

5.2 Future Work

An expansion to the previous functionality exhibited in Figures 2 and 3 could be the inclusion of relevant Authorities to the detected obstacle: if such an AI evaluation system operates in an interoperable digital environment, notifications could be sent *from* and *towards* appropriate city authorities that manage that particular area of the built environment, for example to mark a scheduled future event that would affect physical accessibility to an area, or inversely, for the relevant authority to be notified about a problematic area so that steps can be taken towards alleviating it. Such a design of integrating relevant city authorities would be required to be dynamic, so that if and when relevant authorities change (for example, from City to Municipal level), appropriate adjustments can be made in the system.

In the same vein as interoperability, the reader might have noticed that we omitted O1: *Parked cars on pavement/route* from the final solvable difficulty vector $V_{S(D)}$, as we deem it too dynamic to be effectively solvable. This is mainly because the city of Kavala does not operate a digital parking system - i.e., a system that records and manages where citizens park their cars. Should such a system exist, and as is the case in larger European capitals, our AI system could interlink with it and propose quick remediation (notification sent to the car's owner or the relevant parking authority for quick removal of the obstacle). That would make O1 a *solvable* material element and could mean that it could be included in the solvable difficulties vector.

A final consideration in designing such a system would be the use of pre-recorded data during sample routes, as described, and its possible expansion into additionally utilizing live data from a user en route: such an expansion would again utilize the PwD's smartphone to gather data and correlate it with a recommended route (as per pre-calculation) in real time, enhancing its quality and making adjustments on the go.

Based on the continuous calculation & evaluation model of the AI system through cycles, more services could be offered to the user: e.g., not only to present the situation as it stands right now in an urban area but also alternatives on what route to take that may be preferable to their particular case of disability (e.g. routes that have less difficulty/obstacles but will need a longer time to reach the destination, or routes that are shorter but are more dependent on the person's physical ability & resistance to fatigue) or recommendations & route difficulties that other users have identified themselves en-route (community feedback). Another important consideration is that such an AI system would thrive more as more types of data would be fed into it, to be taken into consideration during calculation cycles, but could work only with a particular set of "essential" data: In essence, a rudimentary evaluation of a route could be calculated using only accelerometer data on the 3-axis plane (based on the realistic movements of a wheelchair), but a more augmented solution would take into consideration headings, elevation, tilt, speed, total time of travel and possibly even "*warnings*" placed by other humans using the same system.

An extra aspect of the proposed system to consider is that, while this discussion foresees it being aimed at urban built environments, it could work to assess the accessibility of natural areas, eco-paths, reserves & green zones. Indeed, areas of green are common route destinations for all social groups, especially denizens of urban areas, and could lead to the AI system being used to calculate excursions & trips to areas external to the immediate built environment of PwDs, extending its value as a socio-economic digital tool.

We additionally note that while an AI system evaluating urban built environments is immediately useful for PwDs in a city, it can also synergize with other social groups that encounter difficulties in urban navigation, such as older adults & seniors, people encountering temporary injuries and as such difficulties in mobility, and even people using grocery carriers or baby strollers within a city.

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