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# Encouraging Eco-Innovative Urban Development

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**Abstract:** This article explores the intertwining connections among artificial intelligence, machine learning, digital transformation, and computational sustainability, detailing how these elements jointly empower citizens within a smart city framework. As technological advancement accelerates, smart cities harness these innovations to improve residents' quality of life. Artificial intelligence and machine learning act as data analysis powerhouses, making urban living more personalized, efficient, and automated, and are pivotal in managing complex urban infrastructures, anticipating societal requirements, and averting potential crises. Digital transformation transforms city operations by weaving digital technology into every facet of urban life, enhancing value delivery to citizens. Computational sustainability, a fundamental goal for smart cities, harnesses artificial intelligence, machine learning, and digital resources to forge more environmentally responsible cities, minimize ecological impact, and nurture sustainable development. The synergy of these technologies empowers residents to make well-informed choices, actively engage in their communities, and adopt sustainable lifestyles. This discussion illuminates the mechanisms and implications of these interconnections for future urban existence, ultimately focusing on empowering citizens in smart cities.

**Keywords:** smart cities; artificial intelligence; machine learning; digital transformation; computational sustainability; logic programming; the laws of thermodynamics; entropy

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## 1. Introduction

In the evolving domain of urban innovation, smart cities (SCs) symbolize a transformative agenda, as described by Batty et al. [1], and further refined by Allam and Newman [2]. Here, the incorporation of technology into urban spaces acts as a propellant for sustainable, efficient living. Anthopoulos [3] underscores this strategy's focus on interconnectivity and sophisticated technology to improve residents' lives. This discourse delves into the synergistic bond between artificial intelligence (AI), machine learning (ML), digital transformation (DT), and computational sustainability (CS)—the four critical tenets shaping the SC concept and enhancing citizen empowerment, resonating with views from Caragliu et al. [4], Angelidou [5], and Bibri and Krogstie [6]. Kitchin [7] observes that the digital age has propelled technology forward, prompting cities worldwide to adopt AI and ML as vital components of urban ingenuity, a sentiment shared by Amović et al. [8]. These tools are proficient at handling large datasets, pivotal for bolstering urban operations, automating processes, and customizing services, as suggested by Komninos et al. [9]. AI and ML also allow urban areas to anticipate societal necessities, oversee intricate systems, and promptly respond to crises, expanding upon Neirotti et al. [10]. Digital transformation extends beyond the scope outlined by Chourabi et al. [11], not merely digitizing public amenities but revolutionizing urban governance and service provision, promoting inclusivity, efficacy, and a citizen-focused approach. Wirtz et al. [12] argue this shift can diminish bureaucratic barriers, enhance transparency, and spur economic growth, advancing the conversation initiated by Batty [13]. CS, a cornerstone of the SC concept emphasized by Albino et al. [14], is crucial amidst pressing environmental challenges. AI, ML, and digital advancements aid in resource optimization, waste reduction, carbon footprint shrinking, and the pursuit of sustainable growth. These initiatives are key in monitoring environmental indicators, endorsing clean energy, refining waste management, and encouraging residents towards sustainable living. At the nexus of AI, ML, DT, and CS lies citizen empowerment in SCs. Harnessing these technological strides, citizens gain the means to make well-informed decisions, actively participate in their communities, and pursue sustainable practices. These technologies afford access to real-time transport data, digital platforms for civic engagement, and bolster an informed, proactive, and resilient populace. This analysis endeavors to unravel the intricate interplay among these intertwined elements and their collective impact on citizen empowerment within SCs. It strives to shed light on these technologies' role in enhancing urban life, navigate the path for cities seeking smart evolution, and underscore pivotal considerations for the future of urban living, a concept emphasized by Meijer and Bolíver [15].

*The Synergy between Sustainable Development, Green Technology, Corporate Social Responsibility, and Innovation*

For a smart city model to be sustainable, it must incorporate environmental considerations (related to CS) alongside innovative practices (related to DT), powered by data-driven decisions (related to AI and/or ML) [16]. Indeed, the intersection of AI, ML, DT, CS, and SC represents a collaborative framework essential for advancing urban innovation [17]. The logical interconnection of these concepts fosters a harmonious blend of technology and sustainability, which is crucial to the development and functioning of SCs [18]. AI and ML serve as the brain of SCs, equipping urban systems with the capability to process vast amounts of data, enabling adaptive and predictive operations [18]. This intelligence is not just about the automation of tasks but extends to the comprehension of patterns and behaviors within an urban context, allowing for the efficient allocation of resources and better decision-making. DT is the circulatory system of this organism, vital for conveying the benefits of technology to every corner of the urban fabric [19]. It facilitates the transition from traditional practices to digitally enabled governance and service delivery, ensuring that efficiency, transparency, and inclusivity are embedded in the city's operations. It is the pathway through which AI and ML solutions reach the hands of citizens and administrators. CS acts as the lungs, ensuring that the city's growth is not at the expense of its environment [20]. Rieder et al. [21] outline how the above-mentioned technological advancements are leveraged to enhance the quality of life for residents, promote efficient and automated urban living, and foster sustainable development. In alignment with the findings of Ortega-Fernández et al. [22], the core argument of the Rieder's study revolves around the symbiotic relationship between technology and urban development, highlighting how AI and ML serve as foundational elements in processing large datasets, automating processes, and personalizing services to meet the dynamic needs of urban populations [21]. Several authors highlight DT as a powerful force that integrates digital technology across all facets of urban life, thereby enhancing value delivery to citizens. These studies underscore the significance of CS in realizing the goal of fostering environmentally responsible and sustainable cities through the efficient utilization of digital resources [23–25].

By utilizing AI and ML, cities can optimize energy consumption, reduce waste, and promote sustainable practices, making the city not only smarter but also greener. SCs, as the tangible manifestation of these combined efforts, embody the holistic body that benefits from the synergies of its parts. In SCs, citizen empowerment is paramount, the inhabitants are not mere bystanders but active participants, equipped with real-time data and platforms for civic engagement provided through the DT processes. However, if these concepts were to operate in silos without a logical interconnection, there is a risk of creating a semblance of interdependence that is arbitrary and not genuinely integrated. This disjunction can lead to inefficiencies, underutilization of data, and a failure to meet sustainable development goals. Without AI and ML's predictive analytics, DT might only result in superficial changes without deep systemic transformation. Without DT, the advancements of AI and ML would remain inaccessible to the broader population. Without a focus on CS, technological progress could lead to unsustainable practices that harm the environment and society in the long term. Therefore, it is imperative that AI, ML, DT, CS, and SCs not only coexist but are deeply intertwined, each reinforcing the other to create a robust, responsive, and sustainable urban ecosystem. The synergy among these components is what allows for the intelligent evolution of cities, fostering environments where technology serves the people and the planet in a balanced and thoughtful manner. SCs thrive on this interconnectedness; it is the bedrock of their innovation, ensuring that technological advancements equate to an improved quality of life for all citizens.

## 2. Exploring the Influence of Entropy in Knowledge Expression and Logical Discourse

The study introduces a novel methodology for evaluating entropic efficiency in problem-solving scenarios. It builds on the concept that entropy ranges between 0 and 1, with lower values indicating order and higher ones reflecting disorder [26–28]. Situated in the realm of Knowledge Representation and Reasoning (KRR) within AI, the focus is on structuring knowledge for computational interpretation and developing algorithms for intelligent decision-making using such knowledge [29]. KRR employs formal languages like First-Order Logic, Description Logics, and frame-based systems for organizing information, which reasoning algorithms then utilize to answer queries and tackle complex challenges. The methodology draws an analogy between KRR and thermodynamics, likening the process of energy degradation to the way usable energy decreases over time, an idea echoing the First and Second Laws of Thermodynamics. The First Law dictates energy conservation within an isolated system, implying energy transformation rather than loss. The Second Law introduces entropy as a measure of systemic order, delineating the natural trend towards disorder [30,31]. In KRR, the entropic state signifies the quantum of energy that diminishes yet never vanishes entirely [27,32]. This is characterized, viz.

- Exergy, reflecting the portion of energy that can be harnessed;
- Vagueness, denoting the potential energy that could have been exploited; and
- Anergy, indicating the potential of energy that remains unutilized.

KRR methodologies, especially in Model Theory [33,34] and Proof Theory [35,36], intertwine with Logic Programming (LP) principles. The paper leverages a Proof Theoretical framework to extend the LP paradigms for problem resolution. It develops a Logic Program with a well-defined set of clauses or archetypes to exemplify the application of these theories (Program 1) [36,37], viz.

**Program 1.** *The quintessential instance of a logical entity.*

$$
\begin{array}{l}
\{ \\
\quad \neg\ p\ \leftarrow \mathit{not}\ p,\ \mathit{not}\ \mathit{exception}_p \\
\quad p\ \leftarrow p_1, \ldots, p_n,\ \mathit{not}\ q_1, \ldots, \mathit{not}\ q_m \\
\quad ?\ (p_1,\ \ldots,\ p_n,\ \mathit{not}\ q_1,\ \ldots,\ \mathit{not}\ q_m)\ (n,\ m\ \geq 0) \\
\quad \mathit{exception}_{p_1},\ \ldots,\ \mathit{exception}_{p_j}\ (0\ \leq\ j\ \leq k)\ \textit{being k an integer number} \\
\}
\end{array}
$$

This approach integrates foundational ground literals and assertive propositions, along with negation-as-failure—a principle asserting that a proposition is deemed false if it cannot be proven true due to the absence of explicit evidence [36]. Within this structure, each program comprises a set of abducibles, which are hypotheses or assumptions used as exceptions to the standard extensions of the predicates shaping the program's logic framework [33,38], viz.

$$\text{exception}_{p_1}, \ldots, \text{exception}_{p_j} \ (0 \le j \le k) \text{ being k an integer number}$$

This data captures crucial details, insights, or specific elements that are indispensable. Meanwhile, certain types of clauses serve as integrity constraints or invariants which supply the necessary context for understanding the universe of discourse, viz.

$$?\ (p_1, \ldots, p_n, \text{not } q_1, \ldots, \text{not } q_m)\ (n, m \ge 0)$$

The structuring of knowledge for computational interpretation and algorithm development for intelligent decision-making benefits from integrating Computational Collective Intelligence with diverse disciplines such as Knowledge Representation, Thermodynamics, and Mathematical Logic [39,40]. This integrated approach demonstrates remarkable flexibility and effectiveness across different scenarios, making it universally applicable to any case study [41,42]. The core of this approach is its interdisciplinary nature, which leverages the principles of thermodynamics as a metaphorical lens for AI performance and constraints [43]. This approach is not only novel but also highly adaptable, making it suitable for a variety of case studies [44]. For instance, the integration of KRR with thermodynamic concepts allows for a dynamic assessment of AI systems, focusing on energy efficiency and entropy, the key factors in determining system performance and sustainability [44]. Several other case studies can be referenced, particularly those involving, namely:

Complex Data Environments—In these cases, the approach's emphasis on energy efficiency (borrowed from thermodynamics) can guide the structuring of AI systems to handle and process large datasets more efficiently [45]. This is particularly relevant in fields like big data analytics and cloud computing, where managing computational resources effectively is crucial [46].

Decision-Making Systems—The incorporation of mathematical logic into the problem-solving framework enhances AI's decision-making capabilities. In case studies focused on autonomous vehicles or financial systems, where precision and reliability are paramount, the rigorous logical frameworks ensure that the AI's decisions are both sound and verifiable [46].

Dynamic and Evolving Systems—This approach's adaptability makes it ideal for applications in environments that are not static but require continuous learning and adaptation. Case studies in robotics or adaptive learning systems can benefit from this approach, as it supports the development of AI that can evolve and respond to changing conditions without human intervention [47].

Interdisciplinary Integration—The ability to integrate various disciplines ensures that the approach can be applied in a broad range of case studies, from healthcare to environmental science. This flexibility is essential for developing holistic AI solutions that consider multiple aspects of a problem, such as ethical considerations, sustainability, and technical feasibility [48].

## 3. The Role of Thermodynamics in Data Procurement and Judgement

In the rapidly advancing domain of data science, the groundbreaking method of applying thermodynamic concepts to data collection and analysis presents an innovative perspective on data comprehension and application. This approach interestingly draws comparisons between the principles of thermodynamics, particularly regarding energy and work, and the practices of gathering and analyzing data. While non-traditional, the belief is that such a comparison will pique the reader's interest. Additionally, the incorporation of AI, ML, and DT within this framework promotes sustainability and enhances citizen empowerment in a SC context. The application of thermodynamics to data collection and analysis signifies an extraordinary convergence of distinct disciplines, providing a novel angle that could further strengthen the role of AI, ML, and DT in forging sustainable initiatives, thus reinforcing citizen engagement in the smart city infrastructure.

*Enhancing Citizen Agency in Smart Urban Environments*

Artificial intelligence, machine learning, digital transformation, and computational sustainability are pivotal in advancing smart city initiatives. These technologies greatly improve citizens' ability to interact with and impact their urban environments. AI and ML are instrumental in gathering and analyzing urban data, empowering people to navigate the complexities of city life. AI decodes complex patterns, from traffic circulation to air quality, enabling informed decisions. ML enhances this with predictive models that forecast urban developments, promoting a forward-thinking community. DT and CS are transformative, making vast data sets actionable through digital platforms, allowing citizens to access real-time updates and partake in civic engagement, from urban planning to energy use. This integration turns citizens from mere spectators into active contributors, revitalizing democratic engagement in cities. It lifts citizen involvement, leveraging data for civic engagement and empowerment. Indeed, the goal is to evolve the urban experience into a collaborative creation by its residents, thanks to AI, ML, DT, and CS. This interplay is reshaping urban life, creating a milieu for an informed, involved citizenry. The vision of an informed, proactive urban community is materializing as these tools lay the groundwork for an interactive, responsive urban existence. The influence of these technologies on citizen involvement in SCs invites further exploration, especially through entropic methods in KRR, which could further enhance the empowerment process. This leads to a critical inquiry:

> *How might entropic methodologies in KRR intensify citizen empowerment within the Smart City architype?*

Offering a clear-cut response to this question is complex, as it hinges on the particularities of the urban setting and the diversity of its population. Nevertheless, several possibilities can be considered. For instance, the pertinence of each answer may need to be adjusted to fit the specific scenario, suggesting that reactions should be customized to reflect the subtleties of the inquiry at hand.

## 4. Methodology

This section briefly summarizes the study design, data collection procedure, instruments employed, sample characteristics, and data analysis methods. It also touches upon the ethical considerations observed during the research.

### *4.1. Study Design*

Technological advancements act as a driving force in various domains such as urban management, innovation, job creation, industry growth, and environmental sustainability, among others. However, there remains public apprehension regarding the role of the connections among AI, ML, DT, and CS, in the empowerment of citizens within a smart city framework. To tackle this challenge, evaluating the understanding and acceptance of these technologies is essential, which entails active involvement from the population. Therefore, this study aims to evaluate the perception of the Portuguese population regarding the role of the connections among of these technologies in a smart city framework. With this goal in consideration, a questionnaire was developed and distributed in Portugal to a cross-section of individuals, incorporating male and female genders and diverse ages. Addressing five key topics (artificial intelligence and machine learning awareness and usage, digital transformation perception and use, citizen empowerment and perception, and correlation perception), the questionnaire was structured to facilitate the application of the methodology proposed in [49] for transforming non-numeric information into numeric data.

### 4.2. Data Collection

The choice of a questionnaire survey method arose from a thorough examination of available techniques, with the decision bolstered by its simplicity and adaptability. Although questionnaire surveys may lack depth and context, they provide efficiency, standardization, and anonymity.

The questionnaire devised for this study was divided into two segments. The first segment aimed to gather sociodemographic information, encompassing details like age, gender, and educational background. The second segment delved into a series of statements exploring the core topics under investigation (i.e., artificial intelligence and machine learning awareness and usage (AI and ML—4); digital transformation perception and use statements (DT and US—5); citizen empowerment and perception statements (CE and PS—4); and correlation perception statements (CPS—4), for which participants were prompted to select the option(s) that align with their opinions on each statement. Furthermore, they were also requested to indicate the progression tendency of his/her answer, i.e., an increasing tendency (strongly disagree → strongly agree) or the opposing (strongly agree → strongly disagree) as shown in Figure 1.

**PART II**

For each statement tick with × the option(s) that best reflects your opinion. Please also indicate the progression tendency of your answer, i.e., an increasing tendency (Strongly Disagree → Strongly Agree) or the opposing (Strongly Agree → Strongly Disagree).

| | Strongly Agree | Agree | Disagree | Strongly Disagree | Increasing Tendency | Decreasing Tendency |
|---|---|---|---|---|---|---|
| **Artificial Intelligence and Machine Learning Awareness and Usage – 4 Items** | | | | | | |
| S1. I am familiar with the terms "Artificial Intelligence" and "Machine Learning". | ☐ | ☒ | ☒ | ☐ | ☒ | ☐ |
| S2. I have utilized tools or applications that incorporate artificial intelligence and/or machine learning. | ☐ | ☒ | ☐ | ☐ | ☒ | ☐ |
| S3. I use artificial intelligence and/or machine learning tools or applications, such as voice assistants or recommendation systems. | ☐ | ☐ | ☒ | ☒ | ☐ | ☒ |
| S4. I believe the artificial intelligence and/or machine learning applications I use have contributed to making my life easier or more efficient. | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
| **Digital Transformation Perception and Use Statements – 5 Items** | | | | | | |
| S5. I am familiar with the term "Digital Transformation". | ☐ | ☐ | ☐ | ☒ | ☐ | ☒ |
| S6. I can name several tools or services I use that have undergone digital transformation. | ☐ | ☐ | ☒ | ☐ | ☒ | ☐ |
| S7. I regularly use digital tools or platforms in my daily life. | ☐ | ☐ | ☒ | ☐ | ☒ | ☐ |
| S8. I am aware of the impact of digital tools/platforms on my life. | ☒ | ☐ | ☐ | ☐ | ☒ | ☐ |
| S9. I believe digital transformation has significantly impacted the way I interact with institutions. | ☒ | ☐ | ☐ | ☐ | ☒ | ☐ |
| **Citizen Empowerment and Perception Statements – 4 Items** | | | | | | |
| S10. I am confident in my understanding of "Citizen Empowerment". | ☐ | ☐ | ☐ | ☒ | ☒ | ☐ |
| S11. I feel empowered as a citizen in my daily life. | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
| S12. I can name specific instances or tools that have contributed to my feeling of empowerment. | ☐ | ☒ | ☐ | ☐ | ☒ | ☐ |
| S13. I am satisfied with my degree of empowerment. | ☐ | ☐ | ☒ | ☐ | ☒ | ☐ |
| **Correlation Perception Statements – 4 Items** | | | | | | |
| S14. I believe there is a connection between the use of artificial intelligence, machine learning, and digital transformation and my level of empowerment as a citizen. | ☐ | ☐ | ☒ | ☐ | ☒ | ☐ |
| S15. I can share specific examples where I feel artificial intelligence, machine learning, digital transformation, and computational sustainability have contributed to my empowerment. | ☐ | ☐ | ☐ | ☒ | ☒ | ☐ |
| S16. I see potential benefits with the increased integration of artificial intelligence, machine learning, digital transformation, and computational sustainability in everyday life. | ☐ | ☒ | ☒ | ☐ | ☐ | ☒ |
| S17. I believe in the future role of artificial intelligence, machine learning, digital transformation, and computational sustainability in citizen empowerment. | ☐ | ☐ | ☒ | ☐ | ☒ | ☐ |

**Figure 1.** The preferences expressed by participant one in response to the second part of the questionnaire.

Each core topic is crafted to gauge aspects related to the role of the connections among artificial intelligence, machine learning, digital transformation, and computational sustainability, in the empowerment of citizens within a smart city framework. The statements associated with each of the topics mentioned earlier can be found in Figure 1. The primary goal of the AI and ML—4 topic is to comprehend and scrutinize various critical elements regarding the participant's awareness of AI and ML. It focuses on how people perceive and utilize these technologies, as well as associated tools and services. The statements included in this topic endeavors to assess awareness, gauge usage levels, identify emerging trends, evaluate public perception, understand the overall impact, inform strategic decision-making, and guide the development of policies and regulatory frameworks. Regarding the topic DT and US—5, the expectation is that the researcher team will be able to extract significant understanding of the public's grasp on and opinions about DT, particularly its effects on daily life and interactions with different entities. This knowledge is likely to be instrumental in formulating strategies for communication and education related to DT. These strategies will aim to improve public awareness of DT, assess the degree of its implementation and user engagement, identify the impact as perceived by users, and measure the quality of interactions between individuals and organizations. Concerning the topic CE and PS—4, this set of statements is primarily designed to explore the public's sense of empowerment as individuals within society. It aims to determine the contributing factors to this sentiment, identify potential areas for enhancement, and collate data that may aid in the creation of more effective strategies to boost citizen empowerment. This includes examining the concept of "empowerment" from diverse perspectives, how individuals encounter it in their daily existence, pinpointing tools or instances that intensify this sensation, and assessing the level of empowerment individuals perceive across different facets of their life. Finally, the set of statements included in the topic CPS—4 aims to delve into the public's understanding of the relationship between cutting-edge technologies such as AI, ML, DT, and CS, and the empowerment of citizens. It seeks to explore the potential advantages and limitations, uncover opportunities, and gauge expectations for the future. The questionnaire is structured to gauge the perceived linkage between technology and empowerment, pinpoint moments where empowerment occurs, assess the perceived pros and cons, identify tools that could facilitate empowerment, and understand the anticipations for the future, just to name a few.

Unlike the descriptive nature of the responses in the first segment of the questionnaire, the subsequent segment uses a four-level Likert scale (i.e., strongly agree (4), agree (3), disagree (2), and strongly disagree (1)).

The questionnaires were administered monthly for a period of 6 months, spanning from January 2023 to June 2023. Each participant received a hard copy of the questionnaire in person. All 73 distributed questionnaires were returned, resulting in a 100% return rate. The questionnaire was answered anonymously, and all participants agreed to participate over a period of 6 months by completing the questionnaire monthly. The participants received a secret personal code when they first answered the questionnaire, enabling researchers to identify responses from the same participant across multiple instances.

### 4.3. Participants

The study comprised an opportunity sample of 73 participants who completed the questionnaire during the study period. The age of the participants ranged from 18 to 65 years (with a mean age of 39.6 years), with 53.4% being women and 45.6% men.

### 4.4. Qualitative Data Processing

The information obtained in the second segment of the questionnaire uses a four-level Likert scale (i.e., strongly agree (4), agree (3), disagree (2), and strongly disagree (1)). However, since the tendency of progression of the participant's response was also asked, the Likert scale can be expanded to consider seven levels:

*Strongly Agree (4), Agree (3), Disagree (2), Strongly Disagree (1), Disagree (2), Agree (3), Strongly Agree (4)*

The expanded Likert scale should be read either from left to middle, indicating a progression from strongly agree (4) to strongly disagree (1), or from middle to right, indicating a progression from strongly disagree (1) to strongly agree (4). The first reading suggests a shift towards a more negative perspective or a disagreement with the statements presented, whereas the second suggests a shift towards a more positive perspective or an agreement with the statements.

Following the methodological framework introduced in [49], the non-numeric information was transformed into numerical information. In accordance with this methodology, the $z$ responses associated with each theme are visualized in a circle with a radius of $1/\sqrt{\pi}$. Within the circle, $z$ sections are delineated, with a mark on the axis indicating each response option, as described in Section 5.

### *4.5. Ethical Aspects*

The research was conducted in accordance with existing legal norms and ethical standards. All participants were informed about the research objectives and voluntarily agreed to take part by filling out the questionnaire.

## 5. Case Study

The role of the connections among AI, ML, DT, and CS in the empowerment of citizens within a smart city framework were examined at the individual level. Thus, Table 1 presents the responses of participant one to the second segment of the questionnaire during the study period, taking into account the expanded Likert scale. For example, for the AI and ML—4 topic at month 0 the answer to S1 was Disagree (2)—Agree (3), indicating a decrease in entropy, since there is an increasing tendency in his/her opinion. For S2, the answer was Agree (3), a fact that speaks for itself. For S3, the answer was Disagree (2)—Strongly Disagree (1), indicating an increase in entropy, since there is a decreasing tendency in his/her opinion. Finally, for S4 no options were marked, corresponding to a vague situation. In this case, although the values of the different forms of energy (i.e., exergy, vagueness, and anergy) are unknown, it is known that the bandwidth is the interval [0, 1].

**Table 1.** The answers of participant one to the topics artificial intelligence and machine learning awareness and usage (AI and ML—4), digital transformation perception and use statements (DT and US—5), citizen empowerment and perception statements (CE and PS—4), and correlation perception statements (CPS—4), over a six-month period.

| Month | Topic | Statements | Expanded Likert Scale 7 Items * | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | 4 | 3 | 2 | 1 | 2 | 3 | 4 | Vagueness |
| 0 | AI and ML—4 | S1 | | | | | × | × | | |
| | | S2 | | | | | | × | | |
| | | S3 | | | × | × | | | | |
| | | S4 | | | | | | | | × |
| | DT and US—5 | S5 | | | | × | | | | |
| | | S6 | | | | | × | | | |
| | | S7 | | | | | × | | | |
| | | S8 | | | | | | | × | |
| | | S9 | | | | | | | × | |
| | CE and PS—4 | S10 | | | | × | | | | |
| | | S11 | | | | | | | | × |
| | | S12 | | | | | | × | | |
| | | S13 | | | | | × | | | |

**Table 1.** *Cont.*

| Month | Topic | Statements | Expanded Likert Scale 7 Items * | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | **4** | **3** | **2** | **1** | **2** | **3** | **4** | **Vagueness** |
| 0 | CPS—4 | S14 | | | | | × | | | |
| | | S15 | | | | × | | | | |
| | | S15 | | × | × | | | | | |
| | | S17 | | | | | × | | | |
| 1 | AI and ML—4 | S1 | | | | | × | | | |
| | | S2 | | | | | | × | | |
| | | S3 | | | | × | × | | | |
| | | S4 | | | | | × | | | |
| | DT and US—5 | S5 | | | | | × | | | |
| | | S6 | | | | | | × | | |
| | | S7 | | | | | × | × | | |
| | | S8 | | | | | | × | | |
| | | S9 | | | | | | | × | |
| | CE and PS—4 | S10 | | | | × | | | | |
| | | S11 | | | | × | | | | |
| | | S12 | | | | | | × | | |
| | | S13 | | | | × | | | | |
| | CPS—4 | S14 | | | | | × | × | | |
| | | S15 | | | × | | | | | |
| | | S15 | | | | | × | × | | |
| | | S17 | | | | | | × | | |
| 2 | AI and ML—4 | S1 | | | | | | × | | |
| | | S2 | | | | | | | × | |
| | | S3 | | | | | | × | | |
| | | S4 | | | | × | | | | |
| | DT and US—5 | S5 | | | | | × | | | |
| | | S6 | | | | | | × | | |
| | | S7 | | | | | | × | | |
| | | S8 | | | | | | | × | |
| | | S9 | | | | | | | × | |
| | CE and PS—4 | S10 | | | | | × | | | |
| | | S11 | | | | | × | | | |
| | | S12 | | | | | × | | | |
| | | S13 | | | | × | | | | |
| | CPS—4 | S14 | | | | | | × | | |
| | | S15 | | | × | | | | | |
| | | S15 | | | | | × | × | | |
| | | S17 | | | | | | × | | |
| 3 | AI and ML—4 | S1 | | | | | | × | | |
| | | S2 | | | | | | | × | |
| | | S3 | | | | | | × | × | |
| | | S4 | | | × | | | | | |
| | DT and US—5 | S5 | | × | × | | | | | |
| | | S6 | | | | | × | × | | |
| | | S7 | | | | | × | | | |
| | | S8 | | | | | | × | | |
| | | S9 | | | | | | × | | |
| | CE and PS—4 | S10 | | | | | × | | | |
| | | S11 | | | | | × | × | | |
| | | S12 | | | | × | | | | |
| | | S13 | | | × | | | | | |

**Table 1.** *Cont.*

| Month | Topic | Statements | Expanded Likert Scale 7 Items * | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | 4 | 3 | 2 | 1 | 2 | 3 | 4 | Vagueness |
| 3 | CPS—4 | S14 | | | | | | × | | |
| | | S15 | | × | × | | | | | |
| | | S15 | | | | | | | × | |
| | | S17 | | | | | | | × | |
| 4 | AI and ML—4 | S1 | | | | | | × | × | |
| | | S2 | | | | | | | × | |
| | | S3 | | | | | | | × | |
| | | S4 | | × | × | | | | | |
| | DT and US—5 | S5 | | | × | | | | | |
| | | S6 | | | | | | × | × | |
| | | S7 | | | | | | × | | |
| | | S8 | | | | | | × | | |
| | | S9 | | | | | | | × | |
| | CE and PS—4 | S10 | | | | | × | × | | |
| | | S11 | | | | | | × | | |
| | | S12 | | | | | × | | | |
| | | S13 | | | × | | | | | |
| | CPS—4 | S14 | | | | | | × | × | |
| | | S15 | | × | × | | | | | |
| | | S15 | | | | | | | × | |
| | | S17 | | | | | | × | | |
| 5 | AI and ML—4 | S1 | | | | | | | × | |
| | | S2 | | | | | | | × | |
| | | S3 | | | | | | × | × | |
| | | S4 | | × | | | | | | |
| | DT and US—5 | S5 | | | × | | | | | |
| | | S6 | | | | | | | × | |
| | | S7 | | | | | | × | × | |
| | | S8 | | | | | | | × | |
| | | S9 | | | | | | | × | |
| | CE and PS—4 | S10 | | | | | | × | | |
| | | S11 | | | | | | × | | |
| | | S12 | | | | | | × | | |
| | | S13 | | × | × | | | | | |
| | CPS—4 | S14 | | | | | | × | | |
| | | S15 | | × | | | | | | |
| | | S15 | | | | | | × | × | |
| | | S17 | | | | | | × | | |

* (1) Strongly Disagree, (2) Disagree, (3) Agree, (4) Strongly Agree.

The shapes in Figure 2 represent the visual interpretation of participant one's answers to the topics AI and ML—4, DT and US—5, CE and PS—4, and CPS—4, at month 0, for both the Best-Case Scenario (BCS) and the Worst-Case Scenario (WCS). In Figure 2, the dark areas symbolize exergy, representing high-energy states or useful energy, the grey areas indicate vagueness, suggesting uncertainty or areas of indeterminate energy states, and the white ones stand for anergy, or areas where energy cannot be harnessed for work [49–51].

The assessment of the areas shown in Figure 2, for the BCS and for the WCS are provided in Tables 2 and 3, respectively, for both scales, i.e., from strongly agree (4) to strongly disagree (1), and from strongly disagree (1) to strongly agree (4).

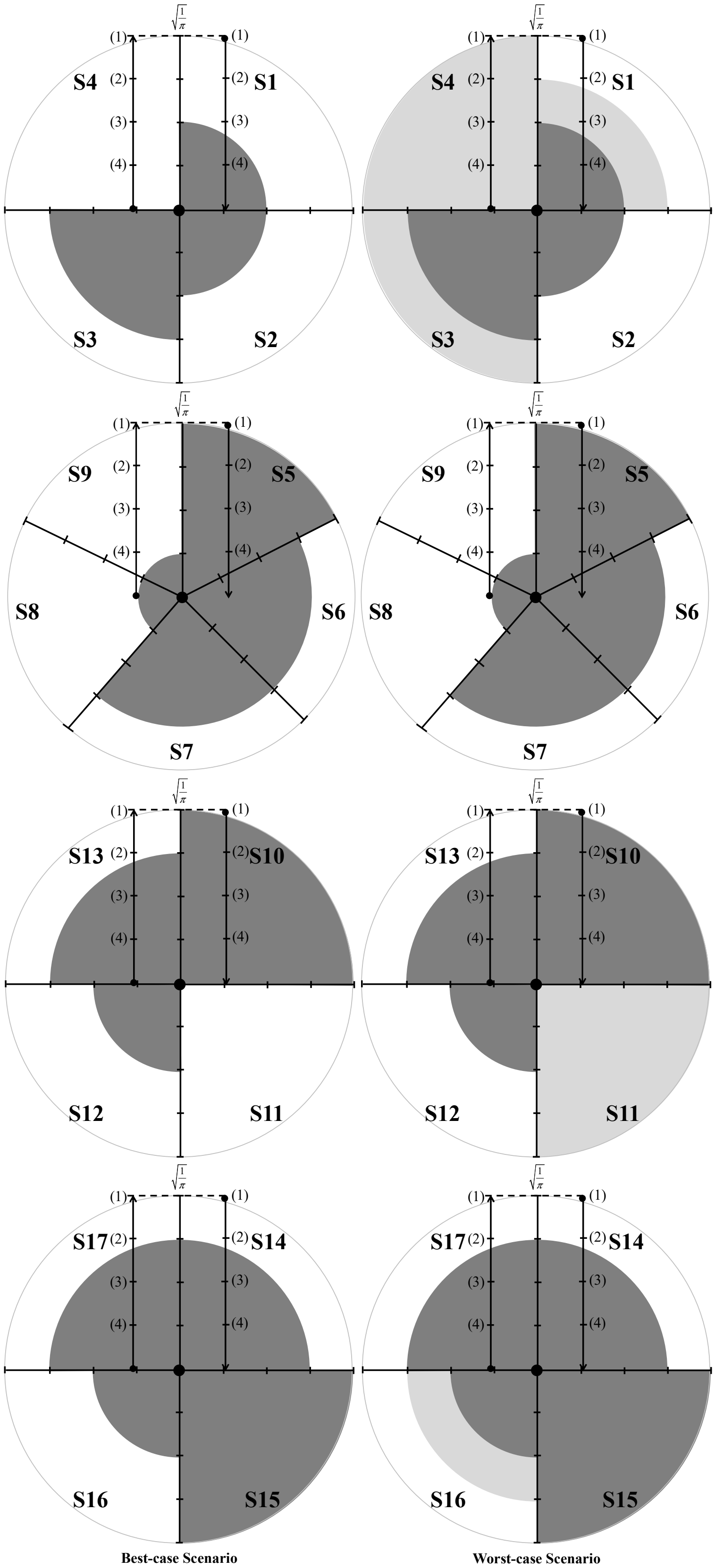


**Figure 2.** A pictorial reading of the participant one answers to the statements S1 to S17, in the best-case and worst-case scenarios at month 0. The dark, gray, and white colored areas correspond to exergy, vagueness, and anergy, respectively.

**Table 2.** Evaluation of exergy, vagueness, and anergy for artificial intelligence and machine learning awareness and usage (AI and ML—4) topic in month 0, in the best-case scenario, for both scales, i.e., from strongly agree (4) to strongly disagree (1), and from strongly disagree (1) to strongly agree (4).

| Statement | AI and ML—4—Scale (4) (3) (2) (1) | AI and ML—4—Scale (1) (2) (3) (4) |
|---|---|---|
| S1 | – | $exergy_{S_1} = -\frac{1}{4}\pi r^2\Big]_{\frac{2}{4}\sqrt{\frac{1}{\pi}}}^{0} = -\frac{1}{4}\pi r^2\Big]_{\frac{2}{4}\sqrt{\frac{1}{\pi}}}^{0} = \pi\left(0-\left(\frac{2}{4}\sqrt{\frac{1}{\pi}}\right)^2\right) = 0.06$ |
| | – | $vagueness_{S_1} = -\frac{1}{4}\pi r^2\Big]_{\frac{2}{4}\sqrt{\frac{1}{\pi}}}^{\frac{2}{4}\sqrt{\frac{1}{\pi}}} = 0$ |
| | – | $anergy_{S_1} = -\frac{1}{4}\pi r^2\Big]_{\frac{2}{4}\sqrt{\frac{1}{\pi}}}^{\sqrt{\frac{1}{\pi}}} = 0.19$ |
| S2 | – | $exergy_{S_2} = -\frac{1}{4}\pi r^2\Big]_{\frac{2}{4}\sqrt{\frac{1}{\pi}}}^{0} = 0.06$ |
| | – | $vagueness_{S_2} = -\frac{1}{4}\pi r^2\Big]_{\frac{2}{4}\sqrt{\frac{1}{\pi}}}^{\frac{2}{4}\sqrt{\frac{1}{\pi}}} = 0$ |
| | – | $anergy_{S_2} = -\frac{1}{4}\pi r^2\Big]_{\frac{2}{4}\sqrt{\frac{1}{\pi}}}^{\sqrt{\frac{1}{\pi}}} = 0.19$ |
| S3 | $exergy_{S_3} = \frac{1}{4}\pi r^2\Big]_{0}^{\frac{3}{4}\sqrt{\frac{1}{\pi}}} = 0.14$ | – |
| | $vagueness_{S_3} = \frac{1}{4}\pi r^2\Big]_{\frac{3}{4}\sqrt{\frac{1}{\pi}}}^{\frac{3}{4}\sqrt{\frac{1}{\pi}}} = 0$ | – |
| | $anergy_{S_3} = \frac{1}{4}\pi r^2\Big]_{\frac{3}{4}\sqrt{\frac{1}{\pi}}}^{\sqrt{\frac{1}{\pi}}} = 0.11$ | – |
| S4 | $exergy_{S_4} = \frac{1}{4}\pi r^2\Big]_{0}^{0} = 0$ | – |
| | $vagueness_{S_4} = \frac{1}{4}\pi r^2\Big]_{0}^{0} = 0$ | – |
| | $anergy_{S_4} = \frac{1}{4}\pi r^2\Big]_{0}^{\sqrt{\frac{1}{\pi}}} = 0.25$ | – |

Similarly, by repeating the calculations presented above, it is possible to compute the values of the different forms of energy, i.e., exergy, vagueness, and anergy for all topics (i.e., AI and ML—4, DT and US—5, CE and PS—4, and CPS—4), for the various months during which the study was conducted, and for all participants. Furthermore, the Degree of Confidence (DoC) was computed according to Figure 3, using Equation (1), and the Quality of Information (QoI) was also computed using Equation (2), with all the findings presented in Table 4, for the BCS.

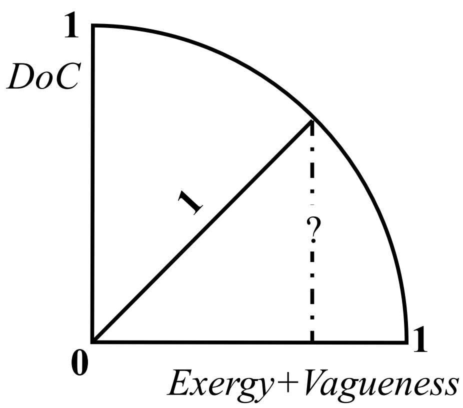


**Figure 3.** Evaluation of the Degree of Confidence (DoC) based on the values of exergy and vagueness.

**Table 3.** Evaluation of exergy, vagueness, and anergy for artificial intelligence and machine learning awareness and usage (AI and ML—4) topic in month 0, in the worst-case scenario, for both scales, i.e., from strongly agree (4) to strongly disagree (1), and from strongly disagree (1) to strongly agree (4).

| Statement | AI and ML—4—Scale (4) (3) (2) (1) | AI andML—4—Scale (1) (2) (3) (4) |
|---|---|---|
| S1 | – | $exergy_{S_1} = -\frac{1}{4}\pi r^2\Big]_{\frac{2}{4}\sqrt{\frac{1}{\pi}}}^{0} = 0.06$ |
| | – | $vagueness_{S_1} = -\frac{1}{4}\pi r^2\Big]_{\frac{2}{4}\sqrt{\frac{1}{\pi}}}^{\frac{3}{4}\sqrt{\frac{1}{\pi}}} = 0.08$ |
| | – | $anergy_{S_1} = -\frac{1}{4}\pi r^2\Big]_{\frac{3}{4}\sqrt{\frac{1}{\pi}}}^{\sqrt{\frac{1}{\pi}}} = 0.11$ |
| S2 | – | $exergy_{S_2} = -\frac{1}{4}\pi r^2\Big]_{\frac{2}{4}\sqrt{\frac{1}{\pi}}}^{0} = 0.06$ |
| | – | $vagueness_{S_2} = -\frac{1}{4}\pi r^2\Big]_{\frac{2}{4}\sqrt{\frac{1}{\pi}}}^{\frac{2}{4}\sqrt{\frac{1}{\pi}}} = 0$ |
| | – | $anergy_{S_2} = -\frac{1}{4}\pi r^2\Big]_{\frac{2}{4}\sqrt{\frac{1}{\pi}}}^{\sqrt{\frac{1}{\pi}}} = 0.19$ |
| S3 | $exergy_{S_3} = \frac{1}{4}\pi r^2\Big]_{0}^{\frac{3}{4}\sqrt{\frac{1}{\pi}}} = 0.14$ | – |
| | $vagueness_{S_3} = \frac{1}{4}\pi r^2\Big]_{\frac{3}{4}\sqrt{\frac{1}{\pi}}}^{\sqrt{\frac{1}{\pi}}} = 0.11$ | – |
| | $anergy_{S_3} = \frac{1}{4}\pi r^2\Big]_{\sqrt{\frac{1}{\pi}}}^{\sqrt{\frac{1}{\pi}}} = 0$ | – |
| S4 | $exergy_{S_4} = \frac{1}{4}\pi r^2\Big]_{0}^{0} = 0$ | – |
| | $vagueness_{S_4} = \frac{1}{4}\pi r^2\Big]_{0}^{\sqrt{\frac{1}{\pi}}} = 0.25$ | – |
| | $anergy_{S_4} = \frac{1}{4}\pi r^2\Big]_{\sqrt{\frac{1}{\pi}}}^{\sqrt{\frac{1}{\pi}}} = 0$ | – |

**Table 4.** Values of EXergy (EX), VAgueness (VA), ANergy (AN), Degree of Confidence (DoC), and the Quality of Information (QoI), regarding participant one, for all topics (i.e., AI and ML—4, DT and US—5, CE and PS—4, and CPS—4) for the study period, in the best-case scenario, for both scales, i.e., from strongly agree (4) to strongly disagree (1), and from strongly disagree (1) to strongly agree (4).

| | | Scale (4) (3) (2) (1) | | | | | | Scale (1) (2) (3) (4) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | EX | VA | AN | DoC | QoI | | EX | VA | AN | DoC | QoI |
| Month 0 | AI and ML—$4_{4\text{–}1}$ | 0.14 | 0 | 0.36 | 0.99 | 0.86 | AI and ML—$4_{1\text{–}4}$ | 0.12 | 0 | 0.38 | 0.99 | 0.88 |
| | DT and US—$5_{4\text{–}1}$ | 0.20 | 0 | 0 | 0.98 | 0.80 | DT and US—$5_{1\text{–}4}$ | 0.25 | 0 | 0.55 | 0.97 | 0.75 |
| | CE and PS—$4_{4\text{–}1}$ | 0.25 | 0 | 0.25 | 0.97 | 0.75 | CE and PS—$4_{1\text{–}4}$ | 0.20 | 0 | 0.30 | 0.98 | 0.80 |
| | CPS—$4_{4\text{–}1}$ | 0.31 | 0 | 0.19 | 0.95 | 0.69 | CPS—$4_{1\text{–}4}$ | 0.28 | 0 | 0.22 | 0.96 | 0.72 |
| | catch-all-clause | 0.22 | 0 | 0.20 | 0.97 | 0.78 | catch-all-clause | 0.21 | 0 | 0.36 | 0.98 | 0.79 |
| Month 1 | AI and ML—$4_{4\text{–}1}$ | – | – | – | – | – | AI and ML—$4_{1\text{–}4}$ | 0.33 | 0 | 0.67 | 0.94 | 0.67 |
| | DT and US—$5_{4\text{–}1}$ | – | – | – | – | – | DT and US—$5_{1\text{–}4}$ | 0.28 | 0 | 0.72 | 0.96 | 0.72 |
| | CE and PS—$4_{4\text{–}1}$ | 0.75 | 0 | 0 | 0.66 | 0.25 | CE and PS—$4_{1\text{–}4}$ | 0.06 | 0 | 0.19 | 1.0 | 0.94 |
| | CPS—$4_{4\text{–}1}$ | 0.14 | 0 | 0.11 | 0.99 | 0.86 | CPS—$4_{1\text{–}4}$ | 0.19 | 0 | 0.56 | 0.98 | 0.81 |
| | catch-all-clause | 0.44 | 0 | 0.06 | 0.83 | 0.56 | catch-all-clause | 0.22 | 0 | 0.54 | 0.97 | 0.78 |
| Month 2 | AI and ML—$4_{4\text{–}1}$ | 0.25 | 0 | 0 | 0.97 | 0.75 | AI and ML—$4_{1\text{–}4}$ | 0.14 | 0 | 0.61 | 0.99 | 0.86 |
| | DT and US—$5_{4\text{–}1}$ | – | – | – | – | – | DT and US—$5_{1\text{–}4}$ | 0.24 | 0 | 0.76 | 0.97 | 0.76 |
| | CE and PS—$4_{4\text{–}1}$ | 0.25 | 0 | 0 | 0.97 | 0.75 | CE and PS—$4_{1\text{–}4}$ | 0.42 | 0 | 0.33 | 0.91 | 0.58 |
| | CPS—$4_{4\text{–}1}$ | 0.06 | 0 | 0.19 | 1.0 | 0.94 | CPS—$4_{1\text{–}4}$ | 0.19 | 0 | 0.56 | 0.98 | 0.81 |
| | catch-all-clause | 0.19 | 0 | 0.06 | 0.98 | 0.81 | catch-all-clause | 0.25 | 0 | 0.57 | 0.95 | 0.75 |
| Month 3 | AI and ML—$4_{4\text{–}1}$ | 0.14 | 0 | 0.11 | 0.99 | 0.86 | AI and ML—$4_{1\text{–}4}$ | 0.09 | 0 | 0.66 | 0.99 | 0.91 |
| | DT and US—$5_{4\text{–}1}$ | 0.05 | 0 | 0.15 | 1.0 | 0.95 | DT and US—$5_{1\text{–}4}$ | 0.26 | 0 | 0.54 | 0.97 | 0.74 |
| | CE and PS—$4_{4\text{–}1}$ | 0.39 | 0 | 0.11 | 0.92 | 0.61 | CE and PS—$4_{1\text{–}4}$ | 0.20 | 0 | 0.30 | 0.98 | 0.80 |
| | CPS—$4_{4\text{–}1}$ | 0.06 | 0 | 0.19 | 1.0 | 0.94 | CPS—$4_{1\text{–}4}$ | 0.09 | 0 | 0.66 | 0.99 | 0.91 |
| | catch-all-clause | 0.16 | 0 | 0.14 | 0.98 | 0.84 | catch-all-clause | 0.16 | 0 | 0.54 | 0.98 | 0.84 |
| Month 4 | AI and ML—$4_{4\text{–}1}$ | 0.06 | 0 | 0.19 | 1.0 | 0.94 | AI and ML—$4_{1\text{–}4}$ | 0.05 | 0 | 0.70 | 1.0 | 0.95 |
| | DT and US—$5_{4\text{–}1}$ | 0.11 | 0 | 0.09 | 0.99 | 0.89 | DT and US—$5_{1\text{–}4}$ | 0.12 | 0 | 0.68 | 0.99 | 0.88 |
| | CE and PS—$4_{4\text{–}1}$ | 0.14 | 0 | 0.11 | 0.99 | 0.86 | CE and PS—$4_{1\text{–}4}$ | 0.27 | 0 | 0.48 | 0.96 | 0.73 |
| | CPS—$4_{4\text{–}1}$ | 0.06 | 0 | 0.19 | 1.0 | 0.94 | CPS—$4_{1\text{–}4}$ | 0.09 | 0 | 0.66 | 0.99 | 0.91 |
| | catch-all-clause | 0.09 | 0 | 0.14 | 1.0 | 0.91 | catch-all-clause | 0.13 | 0 | 0.63 | 0.99 | 0.87 |

**Table 4.** *Cont.*

| | | Scale (4) (3) (2) (1) | | | | | | Scale (1) (2) (3) (4) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | EX | VA | AN | DoC | QoI | | EX | VA | AN | DoC | QoI |
| Month 5 | AI and ML—$4_{4\text{–}1}$ | 0.06 | 0 | 0.19 | 1.0 | 0.94 | AI and ML—$4_{1\text{–}4}$ | 0.05 | 0 | 0.70 | 1.0 | 0.95 |
| | DT and US—$5_{4\text{–}1}$ | 0.11 | 0 | 0.09 | 0.99 | 0.89 | DT and US—$5_{1\text{–}4}$ | 0.05 | 0 | 0.75 | 1.0 | 0.95 |
| | CE and PS—$4_{4\text{–}1}$ | 0.06 | 0 | 0.19 | 1.0 | 0.94 | CE and PS—$4_{1\text{–}4}$ | 0.19 | 0 | 0.56 | 0.98 | 0.81 |
| | CPS—$4_{4\text{–}1}$ | 0.06 | 0 | 0.19 | 1.0 | 0.94 | CPS—$4_{1\text{–}4}$ | 0.14 | 0 | 0.61 | 0.99 | 0.86 |
| | catch-all-clause | 0.07 | 0 | 0.16 | 1.0 | 0.93 | catch-all-clause | 0.11 | 0 | 0.65 | 0.99 | 0.89 |

Similarly, by repeating the calculations presented above, it is possible to compute the values of the different forms of energy, i.e., exergy, vagueness, and anergy for all topics (i.e., AI and ML—4, DT and US—5, CE and PS—4, and CPS—4), for the various months during which the study was conducted, and for all participants. Furthermore, the Degree of Confidence (DoC) was computed according to Figure 3, using Equation (1), and the Quality of Information (QoI) was also computed using Equation (2), with all the findings presented in Table 4, for the BCS.

$$DoC = \sqrt{1 - (exergy + vagueness)^2} \tag{1}$$

$$QoI = 1 - (exergy + vagueness) \tag{2}$$

For both scales, i.e., ranging from strongly agree (4) to strongly disagree (1) and from strongly disagree (1) to strongly agree (4), the values of exergy, vagueness, and anergy presented in Table 4 are the sum of the respective areas. Therefore, in the case of the AI and ML—4 topic in month 0, in the best-case scenario, the value of exergy on the scale from strongly agree (4) to strongly disagree (1) is computed based on the values provided in Table 2.

$$exergy_{4-1} = exergy_{4-1_{S_3}} + exergy_{4-1_{S_4}} = 0.14 + 0 = 0.14$$

whereas for the scale strongly disagree (1) to strongly agree (4) is:

$$exergy_{1-4} = exergy_{1-4_{S_1}} + exergy_{1-4_{S_2}} = 0.06 + 0.06 = 0.12$$

Likewise, the values related to the different forms of energy, DoC, and QoI, for the BCS, were computed for the remaining participants, integrating a database, of which Table 4 represents only an excerpt, since it refers only to participant one. Program 2 describes the answers of participant one using the data provided in Table 4 for month 0.

**Program 2.** *A Logic Programming view of predicates AI and ML—4, DT and US—5, CE and PS—4, and CPS—4's extensions for the best-case scenario at month 0, for participant one.*

{
*/* The sentences below state that the extension of predicates AI and ML—$4_{4\text{–}1}$, ..., cps—$4_{1\text{–}4}$ in best-case scenario are based on explicitly specified clauses and those that cannot be dropped */*

$\neg\, ai\&ml - 4_{4-1}\ (EX,\ VA,\ AN,\ DoC,\ QoI)$

$\leftarrow not\ ai\&ml - 4_{4-1}\ (EX,\ VA,\ AN,\ DoC,\ QoI),$
$not\ exception_{ai\&ml-4_{4-1}}\ (EX,\ VA,\ AN,\ DoC,\ QoI)$

$ai\&ml - 4_{4-1}$ (0.14, 0, 0.36, 0.99, 0.86).
··· *(the dots stand for the remaining predicates$_{4\text{–}1}$ in Table 4)*
}
{
$\neg\, ai\&ml - 4_{1-4}\ (EX,\ VA,\ AN,\ DoC,\ QoI)$

$\leftarrow not\ ai\&ml - 4_{1-4}\ (EX,\ VA,\ AN,\ DoC,\ QoI),$
$not\ exception_{ai\&ml-4_{1-4}}\ (EX,\ VA,\ AN,\ DoC,\ QoI)$

$ai\&ml - 4_{1-4}$ (0.12, 0, 0.38, 0.99, 0.88).
··· *(the dots stand for the remaining predicates$_{1\text{–}4}$ in Table 4)*
}

Similarly, for the WCS, Table 5 presents, for participant one, the different forms of energy, DoC, and QoI for AI and ML—4, DT and US—5, CE and PS—4, and CPS—4, for the various months during which the study was conducted.

**Table 5.** Values of EXergy (EX), VAgueness (VA), ANergy (AN), Degree of Confidence (DoC), and the Quality of Information (QoI), regarding participant one, for all topics (i.e., AI and ML—4, DT and US—5, CE and PS—4, and CPS—4) for the study period, in the worst-case scenario, for both scales, i.e., from strongly agree (4) to strongly disagree (1), and from strongly disagree (1) to strongly agree (4).

| | | Scale (4) (3) (2) (1) | | | | | | Scale (1) (2) (3) (4) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | EX | VA | AN | DoC | QoI | | EX | VA | AN | DoC | QoI |
| Month 0 | AI and ML—$4_{4\text{–}1}$ | 0.14 | 0.36 | 0 | 0.87 | 0.50 | AI and ML—$4_{1\text{–}4}$ | 0.12 | 0.08 | 0.30 | 0.98 | 0.80 |
| | DT and US—$5_{4\text{–}1}$ | 0.20 | 0 | 0 | 0.98 | 0.80 | DT and US—$5_{1\text{–}4}$ | 0.25 | 0 | 0.55 | 0.97 | 0.75 |
| | CE and PS—$4_{4\text{–}1}$ | 0.25 | 0.25 | 0 | 0.87 | 0.50 | CE and PS—$4_{1\text{–}4}$ | 0.20 | 0 | 0.30 | 0.98 | 0.80 |
| | CPS—$4_{4\text{–}1}$ | 0.31 | 0.08 | 0.11 | 0.92 | 0.61 | CPS—$4_{1\text{–}4}$ | 0.28 | 0 | 0.22 | 0.96 | 0.72 |
| | catch-all-clause | 0.22 | 0.17 | 0.03 | 0.91 | 0.61 | catch-all-clause | 0.21 | 0.02 | 0.34 | 0.97 | 0.77 |
| Month 1 | AI and ML—$4_{4\text{–}1}$ | – | – | – | – | – | AI and ML—$4_{1\text{–}4}$ | 0.33 | 0.19 | 0.48 | 0.86 | 0.48 |
| | DT and US—$5_{4\text{–}1}$ | – | – | – | – | – | DT and US—$5_{1\text{–}4}$ | 0.28 | 0.06 | 0.66 | 0.94 | 0.66 |
| | CE and PS—$4_{4\text{–}1}$ | 0.75 | 0 | 0 | 0.66 | 0.25 | CE and PS—$4_{1\text{–}4}$ | 0.06 | 0 | 0.19 | 1.0 | 0.94 |
| | CPS—$4_{4\text{–}1}$ | 0.14 | 0 | 0.11 | 0.99 | 0.86 | CPS—$4_{1\text{–}4}$ | 0.19 | 0.16 | 0.41 | 0.94 | 0.65 |
| | catch-all-clause | 0.44 | 0 | 0.06 | 0.83 | 0.56 | catch-all-clause | 0.22 | 0.10 | 0.44 | 0.94 | 0.68 |
| Month 2 | AI and ML—$4_{4\text{–}1}$ | 0.25 | 0 | 0 | 0.97 | 0.75 | AI and ML—$4_{1\text{–}4}$ | 0.14 | 0 | 0.61 | 0.99 | 0.86 |
| | DT and US—$5_{4\text{–}1}$ | – | – | – | – | – | DT and US—$5_{1\text{–}4}$ | 0.24 | 0 | 0.76 | 0.97 | 0.76 |
| | CE and PS—$4_{4\text{–}1}$ | 0.25 | 0 | 0 | 0.97 | 0.75 | CE and PS—$4_{1\text{–}4}$ | 0.42 | 0 | 0.33 | 0.91 | 0.58 |
| | CPS—$4_{4\text{–}1}$ | 0.06 | 0 | 0.19 | 1.0 | 0.94 | CPS—$4_{1\text{–}4}$ | 0.19 | 0.08 | 0.48 | 0.96 | 0.73 |
| | catch-all-clause | 0.19 | 0 | 0.06 | 0.98 | 0.81 | catch-all-clause | 0.25 | 0.02 | 0.55 | 0.96 | 0.73 |
| Month 3 | AI and ML—$4_{4\text{–}1}$ | 0.14 | 0 | 0.11 | 0.99 | 0.86 | AI and ML—$4_{1\text{–}4}$ | 0.09 | 0.05 | 0.61 | 0.99 | 0.86 |
| | DT and US—$5_{4\text{–}1}$ | 0.05 | 0.06 | 0.09 | 0.99 | 0.87 | DT and US—$5_{1\text{–}4}$ | 0.26 | 0.06 | 0.48 | 0.95 | 0.68 |
| | CE and PS—$4_{4\text{–}1}$ | 0.39 | 0 | 0.11 | 0.92 | 0.61 | CE and PS—$4_{1\text{–}4}$ | 0.20 | 0.08 | 0.22 | 0.96 | 0.72 |
| | CPS—$4_{4\text{–}1}$ | 0.06 | 0.08 | 0.11 | 0.99 | 0.86 | CPS—$4_{1\text{–}4}$ | 0.09 | 0 | 0.66 | 0.99 | 0.91 |
| | catch-all-clause | 0.16 | 0.04 | 0.11 | 0.97 | 0.80 | catch-all-clause | 0.16 | 0.05 | 0.49 | 0.97 | 0.79 |
| Month 4 | AI and ML—$4_{4\text{–}1}$ | 0.06 | 0.08 | 0.11 | 0.99 | 0.86 | AI and ML—$4_{1\text{–}4}$ | 0.05 | 0.05 | 0.66 | 0.99 | 0.90 |
| | DT and US—$5_{4\text{–}1}$ | 0.11 | 0 | 0.09 | 0.99 | 0.89 | DT and US—$5_{1\text{–}4}$ | 0.12 | 0.04 | 0.64 | 0.99 | 0.84 |
| | CE and PS—$4_{4\text{–}1}$ | 0.14 | 0 | 0.11 | 0.99 | 0.86 | CE and PS—$4_{1\text{–}4}$ | 0.27 | 0.08 | 0.41 | 0.94 | 0.65 |
| | CPS—$4_{4\text{–}1}$ | 0.06 | 0.08 | 0.11 | 0.99 | 0.86 | CPS—$4_{1\text{–}4}$ | 0.09 | 0.05 | 0.61 | 0.99 | 0.86 |
| | catch-all-clause | 0.09 | 0.04 | 0.11 | 0.99 | 0.87 | catch-all-clause | 0.13 | 0.06 | 0.58 | 0.98 | 0.81 |
| Month 5 | AI and ML—$4_{4\text{–}1}$ | 0.06 | 0 | 0.19 | 1.0 | 0.94 | AI and ML—$4_{1\text{–}4}$ | 0.05 | 0.05 | 0.65 | 0.99 | 0.90 |
| | DT and US—$5_{4\text{–}1}$ | 0.11 | 0 | 0.09 | 0.99 | 0.89 | DT and US—$5_{1\text{–}4}$ | 0.05 | 0.04 | 0.71 | 0.99 | 0.91 |
| | CE and PS—$4_{4\text{–}1}$ | 0.06 | 0.08 | 0.11 | 0.99 | 0.86 | CE and PS—$4_{1\text{–}4}$ | 0.19 | 0 | 0.56 | 0.98 | 0.81 |
| | CPS—$4_{4\text{–}1}$ | 0.06 | 0 | 0.19 | 1.0 | 0.94 | CPS—$4_{1\text{–}4}$ | 0.14 | 0.05 | 0.56 | 0.98 | 0.81 |
| | catch-all-clause | 0.07 | 0.02 | 0.15 | 0.995 | 0.91 | catch-all-clause | 0.11 | 0.04 | 0.62 | 0.985 | 0.85 |

The values related to the different forms of energy, DoC, and QoI, for the WCS, were also computed for the remaining participants, integrating a database, of which Table 5 represents only an excerpt, since it refers only to participant one. Program 3 describes the answers of participant one using the data provided in Table 5 for month 0.

**Program 3.** *A Logic Programming view of predicates AI and ML—4, DT and US—5, CE and PS—4, and CPS—4's extensions for the worst-case scenario at month 0, for participant one.*

{
/* The sentences below state that the extension of predicates AI and ML—$4_{4\text{–}1}$, ..., cps—$4_{1\text{–}4}$ in worst-case scenario are based on explicitly specified clauses and those that cannot be dropped */

$$\neg\, ai\&ml - 4_{4-1}\ (EX,\ VA,\ AN,\ DoC,\ QoI)$$
$$\leftarrow not\ ai\&ml - 4_{4-1}\ (EX,\ VA,\ AN,\ DoC,\ QoI),$$
$$not\ exception_{ai\&ml-4_{4-1}}\ (EX,\ VA,\ AN,\ DoC,\ QoI)$$
$$ai\&ml - 4_{4-1}\ (0.14,\ 0.36,\ 0,\ 0.87,\ 0.50).$$

$\cdots$ *(the dots stand for the remaining predicates*$_{4-1}$ *in Table 4)*

}
{

$$\neg\, ai\&ml - 4_{1-4}\ (EX,\ VA,\ AN,\ DoC,\ QoI)$$
$$\leftarrow not\ ai\&ml - 4_{1-4}\ (EX,\ VA,\ AN,\ DoC,\ QoI),$$
$$not\ exception_{ai\&ml-4_{1-4}}\ (EX,\ VA,\ AN,\ DoC,\ QoI)$$
$$ai\&ml - 4_{1-4}\ (0.12,\ 0.08,\ 0.30,\ 0.98,\ 0.80).$$

$\cdots$ *(the dots stand for the remaining predicates*$_{1-4}$ *in Table 4)*

}

Aiming to extract specific data or to conduct calculations based on records stored in the database (Tables 4 and 5), Program 4 is presented. It delineates predicates corresponding to each participant entry, establishes specific thresholds for categorization, and integrates rules for the calculation and categorization of averages based on these thresholds. Therefore, within Program 4, one may find:

- Facts (item_score, three arguments): Each fact denotes a score for a topic. The former argument is the topic code, the next one is the participant code, and the last one is the score.
- Retrieving Score (get_item_score, two arguments): This predicate returns the score for a particular participant using its code. The former argument is the participant code, whereas the last one is the score.
- Listing Participants Above a Specific Threshold (participants_above_threshold, two arguments): This predicate returns all participants with scores exceeding the specified threshold via the findall built-in predicate.
- Average Score (average_item_score, one argument): This predicate evaluates the average score for all participants via the built-in predicates.
- Maximum Score (max_item_score, one argument): This predicate returns the maximum score among all participants via the built-in predicate.
- Minimum Score (min_item_score, one argument): This predicate returns the minimum score among all participants via the built-in predicate.

**Program 4.** *An excerpt of the program based on the data provided in Table 4 for managing the participants' answers in the best-case scenario.*

```
% scores for the various topics for participant one at month 0 in the best-case scenario
AI and ML_4_4_1_exergy_score('AI and ML_4_4_1', 'Participant 1', 0.14).
AI and ML_4_1_4_exergy_score('AI and ML_4_1_4', 'Participant 1', 0.12).
AI and ML_4_4_1_vagueness_score('AI and ML_4_4_1', 'Participant 1', 0).
AI and ML_4_1_4_vagueness_score('AI and ML_4_1_4', 'Participant 1', 0).
AI and ML_4_4_1_anergy_score('AI and ML_4_4_1', 'Participant 1', 0.36).
AI and ML_4_1_4_anergy_score('AI and ML_4_1_4', 'Participant 1', 0.38).
AI and ML_4_4_1_doc_score('AI and ML_4_4_1', 'Participant 1', 0.99).
AI and ML_4_1_4_doc_score('AI and ML_4_1_4', 'Participant 1', 0.99).
```

```
AI and ML_4_4_1_qoi_score('AI and ML_4_4_1', 'Participant 1', 0.86).
AI and ML_4_1_4_qoi_score('AI and ML_4_1_4', 'Participant 1', 0.88).
. . . (the dots stand for the predicates DT and US_5_4_1; DT and US_5_1_4; CE and PS_4_4_1;
                                   CE and PS_4_1_4; CPS_4_4_1; and CPS_4_1_4 in Table 4)
% Retrieving the DoC score for a specific participant
get_ doc_score(ParticipantCode, Score): -
    doc_score(ParticipantCode, Score).
% Listing all participants with a DoC score above a specified threshold
participants_above_threshold(Threshold, ParticipantsCodes): -
    findall(ParticipantCode, (doc_score(ParticipantCode, Score), Score > Threshold),
                                                                  ParticipantsCodes).
% Calculating the average DoC score for all participants
average_ doc_score(Average): -
    findall(Score, doc_score(ParticipantCode, Score), Scores),
    sum_list(Scores, Total),
    length(Scores, Count),
    Count > 0, % Prevent division by zero
    Average is Total/Count.
% Finding the maximum DoC score among all participants
max_ doc_score(MaxScore): -
    findall(Score, doc_score(ParticipantCode, Score), Scores),
    max_list(Scores, MaxScore).
% Finding the minimum DoC score among all participants
min_ doc_score(MinScore): -
    findall(Score, doc_score(ParticipantCode, Score), Scores),
    min_list(Scores, MinScore).
% Retrieving the QoI score for a specific participant
get_ qoi_score(ParticipantCode, Score): -
    qoi_score(ParticipantCode, Score).
% Listing all participants with a QoI score above a specified threshold
participants_above_threshold(Threshold, ParticipantsCodes): -
    findall(ParticipantCode, (qoi_score(ParticipantCode, Score), Score > Threshold),
                                                                  ParticipantsCodes).
% Calculating the average QoI score for all participants
average_ qoi_score(Average): -
    findall(Score, qoi_score(ParticipantCode, Score), Scores),
    sum_list(Scores, Total),
    length(Scores, Count),
    Count > 0, % Prevent division by zero
    Average is Total/Count.
% Finding the maximum QoI score among all participants
max_ qoi_score(MaxScore): -
    findall(Score, qoi_score(ParticipantCode, Score), Scores),
    max_list(Scores, MaxScore).
% Finding the minimum QoI score among all participants
min_ qoi_score(MinScore): -
    findall(Score, qoi_score(ParticipantCode, Score), Scores),
    min_list(Scores, MinScore).
```

To illustrate the process of interacting with the database (Tables 4 and 5) using Program 4, several query examples are presented below. These examples emphasize the extraction of specific data or the execution of calculations using the scores:

```
% To obtain the QoI score for the 'Participant 1'
    ?- get_qoi_score('Participant 1', Score).
% To retrieve all participants with a QoI score above 0.75
    ?- participants_ qoi_score_above_threshold(0.75, ParticipantsCodes).
% To compute the average QoI score for all participants
    ?- average_qoi_score(Average).
```

% To retrieve the maximum QoI score among all participants
?- max_qoi_score(MaxScore).
% To retrieve the minimum QoI score among all participants
?- min_qoi_score(MinScore).

The sample queries illustrate the method of engaging with the database to extract specific data or to conduct calculations based on recorded scores. For instance, it is possible to monitor the fluctuations of a participant's entropic state (i.e., exergy + vagueness) and QoI across a six-month span, for the BCS (Figure 4) and for the WCS (Figure 5).

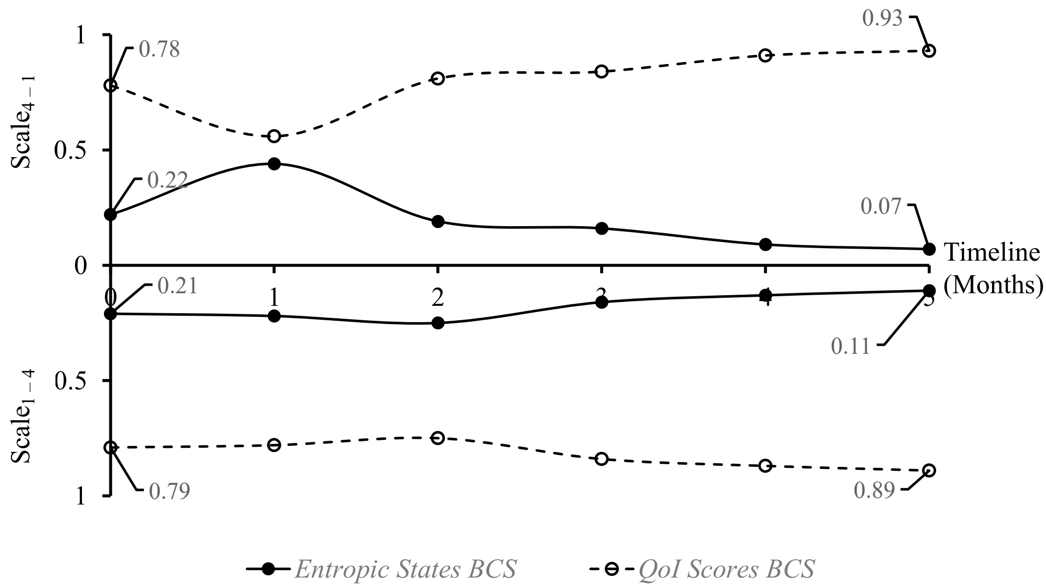


**Figure 4.** The evolution of participant one's Entropic State (ES) and Quality-of-Information (QoI) according to his/her answers within the Best-Case Scenario (BCS) over a six-month period for both scales, i.e., from strongly agree (4) to strongly disagree (1), and from strongly disagree (1) to strongly agree (4).

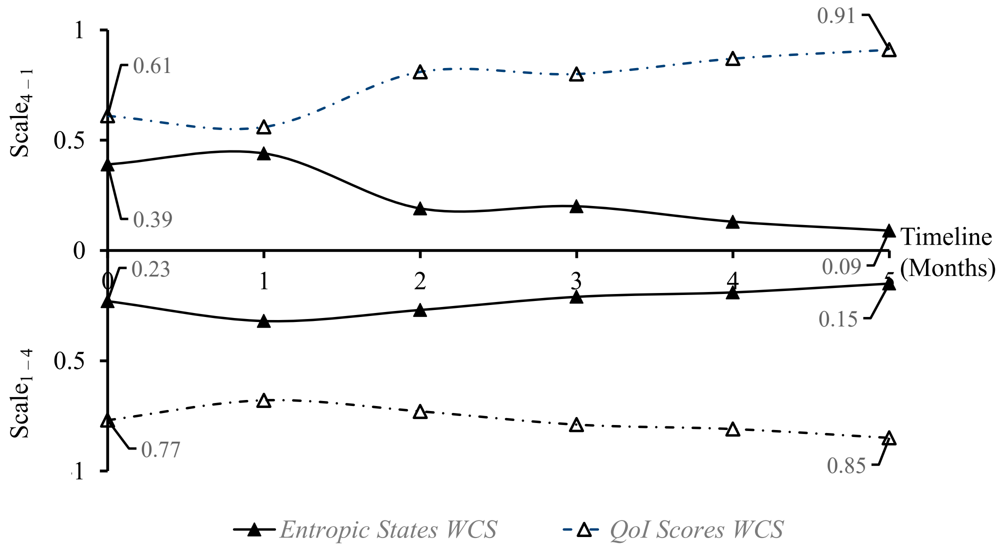


**Figure 5.** The evolution of participant one's Entropic State (ES) and Quality-of-Information (QoI) according to his/her answers within the Worst-Case Scenario (WCS) over a six-month period for both scales, i.e., from strongly agree (4) to strongly disagree (1), and from strongly disagree (1) to strongly agree (4).

When considering the significance of the results obtained from analyzing questionnaire responses over a six-month period within the context of SCs, the essay should explore the reliability and validity of these results to mitigate the influence of arbitrary factors. The study's novel approach to evaluating entropic efficiency in problem-solving scenarios suggests that the methodology is both rigorous and systematic, aiming to reflect the true relationship between the use of technology and citizen empowerment in SCs. Firstly, the significance of the results lies in the consistent trend observed over a sustained period (Figures 4 and 5). This is not a one-off measurement but a pattern emerging from data collected systematically over half a year, reducing the chance of random fluctuations or temporary biases affecting the findings. The geometric interpretation of citizens' entropic states provides a mathematical and visual representation of this evolution, reinforcing the argument that the observed changes are structured and significant. Secondly, the study uses a detailed and well-defined questionnaire, divided into specific topics (i.e., AI and ML—4, DT and US—5, CE and PS—4, CPS—4), to capture the multifaceted impact of technology. This comprehensive approach ensures that a wide range of factors influencing citizen empowerment are considered, which strengthens the argument against arbitrary influences.

The premise that lower entropy values denote order and higher values reflect disorder provides a quantifiable measure of understanding. Participants with structured and consistent responses display low entropy, suggesting a firm grasp of the concepts in question. Conversely, high values of entropy indicate varied and possibly chaotic responses, characteristic of less understanding or misconceptions. The extreme cases, i.e., individuals with no grasp of AI, ML, or DT presented high entropy, their responses lacking coherent structure. In contrast, the experts exhibited low entropy, their responses demonstrating coherent structure and a depth of understanding. The act of completing a questionnaire can raise awareness and pique interest in the topics covered. In this context, participants are nudged to reflect on concepts they might not have otherwise considered, potentially altering their level of understanding. It is essential to consider whether this heightened attention, spurred by the questionnaire itself, constitutes an artificial influence. Arguably, any form of measurement affects the subject being measured, a phenomenon well-documented in quantum mechanics as the observer effect. In the case of completing a questionnaire, this effect could manifest as an increase in the participants' awareness of the topics covered. The act of answering questions about these topics may compel individuals to reflect and thereby deepen their understanding, even if superficially. In the scenario where filling out a questionnaire leads to an enduring engagement with the concepts, fostering continued learning and curiosity, then the influence can be deemed constructive. However, if the impact is fleeting, dissipating soon after the questionnaire is completed, it could be considered artificial, i.e., a transient spike in awareness with no lasting educational value. The entropic approach employed in this study helps to gauge the quality of understanding that arises from this process. By examining the evolution of participants' entropic states over time, the researcher can ascertain whether the questionnaires have a lasting educational effect or merely a momentary one. In summary, the act of filling a questionnaire has the potential to both evaluate and influence the understanding of technical concepts. While there is a risk that the influence could be artificial, it ultimately depends on the persistence of the effect. In the present case, if the engagement with AI, ML, DT, and related concepts continues after the questionnaire filling, it can lead to a genuine enhancement of understanding. Therefore, it is not the immediate influence that should be under scrutiny but the long-term effects on the participants' comprehension and interest in these burgeoning fields of technology. In the future, it would be beneficial to regularly administer the surveys (e.g., every 4 months) after the initial 6-month period to better determine the persistence of the educational impact. Only through longitudinal studies is it possible to truly understand whether the questionnaires are simply catalysts for momentary awareness or effective tools for lasting awareness in complex domains such as AI, ML, and DT, just to name a few.

## 6. Result Analysis

This paper presents an inclusive study that delves into the integration and impact of AI, ML, DT, and CS within the context of SCs. A novel approach is proposed for evaluating entropic efficiency in problem-solving scenarios within AI, drawing parallels between the principles of thermodynamics and the organization of knowledge for computational interpretation. This approach aims to enhance the ability of AI systems to make intelligent decisions based on structured knowledge. Furthermore, the document explores the concept of citizen empowerment within SCs, arguing that the convergence of AI, ML, DT, and CS technologies provides residents with the tools to make informed choices, actively participate in community life, and adopt sustainable behaviors. It suggests that empowerment is pivotal for navigating the complexities of modern urban environments and underscores the potential of these technologies to reshape urban living. This research includes detailed questionnaires aimed at understanding public awareness, perception, and use of AI, ML, and DT technologies. It assesses the impact of these technologies on citizen empowerment and evaluates how they contribute to the creation of smart, sustainable urban ecosystems. Through the analysis of questionnaire answers over several months, the study presents a geometric interpretation of citizens' entropic states, offering insights into the evolving relationship between technology use and empowerment in smart cities. This analytical approach highlights the transformative potential of integrating AI, ML, DT, and CS into urban development strategies, emphasizing the importance of technology in enhancing citizen engagement, sustainability, and the overall quality of urban life.

When analyzing the results of this study, it becomes evident that the achieved outcomes are intertwined with various other research findings, connecting technological advances with enhancements in urban life. Indeed, the present findings align with several works, including Batty et al. [1] who conceptualized SCs as a convergence of digital networks and urban environments, and Allam and Newman [2], who underscored the transformative potential of technology in urban spaces. Additionally, it aligns with results obtained by Anthopoulos [3], who elucidates the interconnected nature of urban technology, thus underlining with the intertwined role of AI and ML as identified in this study. Furthermore, the insights drawn from Caragliu et al. [4] regarding the economic framework of SCs anticipate the economic implications of the current study's results. The implementation of the questionnaire over a period of six months is in line with the ideas presented by Kitchin [7] involving the notion of data-driven cities.

The longitudinal approach used in this study, marked by a geometric interpretation of citizens' entropic states, offers a novel perspective akin to the entropic frameworks presented by Neirotti et al. [10], who explore the informational structure of urban systems. Additionally, this study touches upon the themes of DT and its impact on governance and service delivery, contributing to the discussion initiated by Wirtz et al. [12,52]. These authors explore the idea of cities as platforms for innovation, a concept that the current study reinforces through its exploration of DT's transformative power. The current study also ventures into the realm of CS, a cornerstone of SCs, which echoes the environmental concerns addressed by Albino et al. [14]. The findings presented contribute to this ongoing discourse by showcasing how AI and ML can catalyze resource optimization and waste reduction, thus aligning with the sustainability goals put forth by Bokhari and Myeong [20] in their work on AI in SCs.

The current study contributes to a better understanding of the complexity of urban ecosystems through its innovative entropic approach, thereby complementing the research by Meijer and Bolívar [15], which examines the empirical and normative aspects of SCs. The application of entropy to KRR within the study could also augment the foundational work on KRR methodologies discussed by Lifschitz et al. [42]. In terms of citizen empowerment, the results presented in this study align with the work of Goldsmith et al. [16] where they advocate for the potential of data to enhance citizen participation.

The questionnaire used in this study mirrors this emphasis on engaging citizens, providing empirical data that reinforce the significance of AI, ML, DT, and CS in realizing the vision of responsive and participatory urban spaces. By situating its methodology and results within these contexts, the current study not only reaffirms the findings of its predecessors but also paves the way for future studies. It encourages a deeper probe into the synergies between urban technology and societal benefits, advocating for a continuous dialogue between empirical findings and theoretical advancements. The richness of this comparison highlights the study's intricate relationship with the broader research landscape and its potential to contribute meaningful insights into the interdisciplinary study of SCs and technology's role in urban development and citizen empowerment. It is this interlacing of the study's findings with the work of other authors that propels the academic discussion forward, challenging and refining the understanding of SCs in the age of pervasive technology.

Although this study produced promising findings, it is essential to acknowledge certain limitations that impeded a deeper evaluation of the role of the connections among AI, ML, DT, and CS, in the empowerment of citizens within a smart city framework. The primary constraint stems from the sample size and its nature, i.e., an opportunity sample. By expanding the sample to encompass participants from all regions of Portugal, it becomes feasible to derive results that enable generalization across the entire Portuguese territory. Moreover, gathering additional data on the socio-demographic and socio-economic attributes of the participants will allow a more thorough examination of the factors that could impact the perceptions of the Portuguese population regarding the role of the connections among AI, ML, DT, and CS, in the empowerment of citizens within a smart city framework.

Finally, it is also important to address some possible criticisms/limitations by underscoring the research's intentional focus and the methodological underpinnings that guided the approach. The inherent nature of scholarly research in technology and urban development often carries a forward-looking perspective. This is not to overlook potential drawbacks or challenges but to explore and maximize the capabilities of emerging technologies for societal benefits. The study's positive stance reflects a proactive approach to problem-solving and innovation, a crucial element in the domains of AI, ML, DT, CS, and SCs. It aligns with the aspirational goals of these fields, which seek to harness technology for the greater good, optimize human life, and promote sustainable development. The "dark parts" of these concepts suggests a balanced view that encompasses potential risks, limitations, and negative implications. While this is indeed valuable for a comprehensive overview, the scope of any analysis is bound by its objectives. The optimistic character of the analysis serves a strategic purpose, i.e., to ideate, conceptualize, and propose solutions that can be iteratively refined and critically evaluated in future research. It is part of a strategic view where different studies contribute varying perspectives, eventually creating a balanced understanding. In summary, concerns about exploring the full spectrum of consequences in technological advancements are valid and the positive focus of the study is justified within its context and scope. The research in question serves as a constructive addition to the collective understanding of how emerging technologies can be leveraged for urban and societal betterment. Future research can and should explore the negative implications, as a natural progression of scholarly debate and as a necessary complement to this study.

## 7. Conclusions and Future Work

This work finishes off by synthesizing the impact of integrating artificial intelligence, machine learning, digital transformation, and computational sustainability in smart cities. It emphasizes that these technological pillars are crucial for transforming urban environments into more efficient, personalized, and sustainable habitats. This synergy between technology and urban management empowers citizens by equipping them with the knowledge and tools necessary for engaging actively in their communities and making sustainable choices. Looking forward, the text suggests a roadmap for future research that includes a deeper dive into the confluence of artificial intelligence, machine learning, digital transformation, and computational sustainability within urban ecosystems. It highlights the importance of pioneering more refined methods for analyzing entropic efficiency in artificial intelligence, which could significantly improve the sophistication of knowledge representation and reasoning. This initiative aims to amplify the decision-making capabilities of artificial intelligence systems, making them more responsive and effective in urban settings. Furthermore, it advocates for an interdisciplinary approach to research, blending data science, urban studies, sustainability, and technology development to create smarter, more responsive cities. It proposes an investigation into new strategies for enhancing citizen empowerment through technology, aiming to better understand how these tools can foster greater civic participation, tackle urban issues, and promote sustainable development. This vision for future work underscores the potential of technology to revolutionize city living, making urban areas not just more technologically adept but also more inclusive and conducive to the well-being of all residents. By charting a course for future research and innovation, this study lays the groundwork for the next generation of smart cities that are sustainable, efficient, and empowering for citizens worldwide. Encouraging eco-innovative urban development is a complex endeavor fraught with limitations. However, by proactively identifying these limitations and implementing thoughtful mitigation strategies, cities can navigate these challenges. Mitigation is not merely about addressing current issues but anticipating future ones, ensuring that the smart city framework remains robust, inclusive, and adaptable. Ultimately, by joining innovation with foresight, the goal of sustainable and empowered urban living can be realized. Future research should focus on the longitudinal study of these mitigation strategies, assessing their effectiveness and refining them over time. It should also explore the intersectionality of eco-innovation with socio-economic factors, ensuring that the progress in urban development translates into tangible improvements in the quality of life for all citizens.

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