Enhancement of the Online Presence of Small and Medium Sized Enterprises with Minimum Impact on Traditional Business Activities in Towns and Cities

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Abstract: This paper introduces an innovative strategy for an e-commerce portal designed to support small and medium-sized enterprises (SMEs), integrating local businesses not directly related to product sales, referred to as "satellite businesses", such as bars, restaurants, cinemas or sports facilities. This proposal modifies the existing VR-ZOCO e-commerce portal structure to strengthen local economies, facilitating a symbiosis between online shopping and physical leisure activities. Following a purchase on the portal, users are offered the option to collect their products at specific local points. Linked to this collection act, personalized "leisure plans" are generated, based on "leisure activities" from satellite businesses. This initiative not only promotes the digital growth of SMEs but also encourages the revitalization and sustainable development of local communities. This paper details the fundamental concepts emphasizing how the interaction between online shopping and physical leisure activities can enrich the consumer experience and simultaneously support local businesses. The research proposes a balanced solution that aligns with modern consumer expectations and contributes to local economic and social growth, representing a significant advancement in the digital transformation of SMEs.

1 INTRODUCTION

In today's business landscape, the role of e-commerce is crucial. It acts as a key driver for organizations aiming to expand their market presence and improve operational efficiency (Jain et al., 2021).

E-commerce provides SMEs a chance to boost efficiency and narrow the productivity divide with larger companies (Ministerio de Asuntos Económicos y Transformación Digital, Gobierno de España, 2021). Although the advantages of e-commerce are evident, particularly in the post-COVID era (Pavlova et al., 2021), it brings about notable challenges, particularly for SMEs, such as digital skills deficiency, financial constraints for digital transformation, and difficulty in keeping up with technological advances (Eller et al., 2020).

The digital skills gap is a major hurdle for SMEs and start-ups, impeding their growth and competitiveness. Limited proficiency in digital processes among employees hampers efficiency, innovation, and adaptation to market trends. Addressing this skill deficiency is vital for sustained success in a digitalized business landscape.

On the other hand, the challenge of insufficient funding for digital transformation is a critical issue for SMEs. These businesses often lack the financial resources necessary to undergo digital transformation and to initiate the development of their online presence. This funding gap hinders their ability to adapt to the digital age, where an online presence is increasingly crucial for reaching customers and competing in the market. Without adequate funding, SMEs struggle to invest in necessary technologies, digital marketing, e-commerce platforms, and the training required to effectively utilize these tools. This not only affects their current operations but also impacts their long-term sustainability and growth prospects.

With regard to the last point, the expeditious adoption and integration of technologies such as Artificial Intelligence (AI) and Virtual Reality (VR), are imperative for SMEs within the context of their e-commerce solutions. This proactive approach is necessary to prevent SMEs from consistently falling behind the innovative advancements introduced by larger corporate entities. AI allows for the person-

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alization (Isinkaye et al., 2015), optimization (Goli et al., 2021), and automation of various facets of commerce (Lundström, 2021).

However, it is crucial to emphasize that efforts aimed at the digitization of SMEs, through the establishment of their online presence, should not lead to neglecting their physical operations. The duality between the digital (shopping online) and the physical (in-store shopping) is essential for preserving the local business and the vitality of urban centers. Solely focusing on online commerce could have adverse consequences, contributing to the desertion of urban cores (Zhang et al., 2016) and impacting other associated businesses, such as dining establishments, businesses in the entertainment, culture, and arts sector, sports facilities, and more. In this regard, a balanced strategy that values both digital presence and the maintenance of physical establishments is crucial for the sustainable and harmonious development of SMEs in the contemporary business environment (Helmy Mohamad et al., 2022).

This work introduces an innovative strategy to aid SMEs in embarking on their digital transformation journey. It specifically tackles initial challenges, aiming for seamless integration and balance between physical and online realms. The central goal is to unify traditional urban business activities with electronic commerce, fostering a comprehensive approach to digital integration.

In this context, it is essential to introduce VR-ZOCO, a platform aimed at aiding small businesses in their innovations. VR-ZOCO provides SMEs with the visibility they need through various modules, one of which is the recommendation of leisure plans intertwined with the purchase experience. This paper focuses on elucidating one such module, aimed at enhancing the e-commerce experience for SMEs while ensuring the vitality of their physical presence. The aim is to enhance the user's shopping experience and make the portal a destination for premium and culturally enriched experiences. These efforts are in line with modern consumer expectations and support business growth without compromising local social and economic life.

Following this introduction, the remainder of the paper is organized as follows. Some important concepts, such as "satellite businesses", "leisure activity", "leisure plan" or "user profile" are defined in Section 2. The algorithm suggested to obtain the leisure plans is presented in Section 3. In Section 4, an example of application of the suggested algorithm to generate *leisure plan* is shown. Finally, our conclusions and the future work are presented.

2 FUNDAMENTAL CONCEPTS

This section is dedicated to explain key concepts that will serve as the foundation for a full exploration of the portal. We will look at key terms such as "satellite business", "leisure activity", "user profile", "pickup point" and "leisure plan", providing a concise and essential insight into these fundamental elements within the context of the portal.

2.1 Satellite Business

The satellite businesses within the portal's framework offer users a range of experiences, including cafes, theaters, and sports clubs. These establishments enrich the user experience and contribute significantly to the local economy, infusing vitality into the community. Their range of services aims to meet the needs of users while also encouraging a deeper exploration of the city's cultural and recreational landscape.

In the database, key information about these satellite businesses is meticulously stored to facilitate seamless user interactions and support local economic growth. Crucial data fields include an identifier (*id*) that distinguishes each business uniquely, the business name (*name*) for identification purposes, the physical address for precise location (*address*), and geographical information such as latitude and longitude to facilitate accurate spatial representation (*latitude* and *longitude*). Furthermore, the business credentials, encompassing email (*email*) and password (*pwd*), are stored to ensure security and authentication in interactions with the portal. Formally, a *satellite business* (noted as SB) can be defined as:

$$SB = (id, name, address, latitude, longitude, email, pwd) \tag{1}$$

All satellite businesses in the city that want to offer leisure activities can register on the VR-ZOCO portal. In this way, a number of satellite businesses will exist on the portal, which we will refer to as LSB (i.e. $LSB = \{SB_1, SB_2, \ldots, SB_n\}$).

2.2 Leisure Activity

Leisure activities, orchestrated by the diverse satellite businesses within the portal, constitute a tapestry of engaging events. These carefully curated events go beyond typical product-focused transactions, providing users with a dynamic array of engaging experiences. Whether it is the excitement of a football match, the cultural immersion of a live performance, or the conviviality of a restaurant gathering, leisure activities are intended to captivate and enhance the user experience. The portal will have a list of leisure activities (*LLA*) where the necessary information for each leisure activity (*LA*) can be stored and provided.

Within the database architecture, the organization of data ensures each leisure activity *LA* is seamlessly identified and comprehensively represented. A unique identifier is assigned to each leisure activity (*id*), also an activity description is stored (*description*). It consists of a brief phrase or label that assists in the differentiation of that particular activity from all others. In addition, a business-specific identifier (*id_sb*) is stored to link the leisure activity to the satellite business offering it. Each leisure activity is classified within one or more of the existing product categories on the portal (*category*). The categorization allows users to easily explore a wide range of activities. This flexibility allows the portal to develop leisure plans for users based on a variety of interests. The inclusion of the event date (*date*), along with precise start and end times (*start* and *end*), ensures users are well-informed about the temporal aspects of their chosen plans. Moreover, the "type" designation distinguishes between plans hosted at dedicated facilities and those intrinsic to businesses like restaurants, where the experience is an inherent part of the establishment rather than a scheduled occurrence. Formally *LA* can be defined respectively as follows:

$$LA = (id, description, id\_sb, category, date, start, end, type) \tag{2}$$

In this way, a number of leisure activities will exist on the portal, which we will refer to as *LLA* (i.e. $LLA = \{LA_1, LA_2, \ldots, LA_m\}$).

2.3 User Profile

The user profile will be obtained by a fuzzy clustering algorithm, and it allows us to identify user preferences across different product categories.

First, we compute the different similarity matrices for the relevant characteristic of the user (i.e. his/her preferences, his/her age and his/her previous spending on the portal). In this case, we calculate the following similarity matrices:

- **User Category Preferences (*MP*).** This refers to the matrix that captures the similarity between users based on their preferences across different product categories from C. User preferences are derived from both explicit information provided by user and implicit interactions with products.

  Explicit preferences are obtained directly from user input or feedback. In this context, users fill out a form indicating the categories they are interested in, generating a vector EP of dimensions $|C|$. The user's u_x preferences for each category c_i of C are stored in $EP_{u_x}[i]$. A value of 0 will be used in categories where the user has no interest and a value greater than 0 in those where the user does have some interest (i.e. $EP_{u_x}[i] \in [0,1]$).

  Implicit preferences, on the other hand, are inferred from the user's behaviour on the portal, taking into account aspects such as purchase history (P) or browsing patterns, such as 3D manipulation (M), viewing (V) and teleportation (T) in each category $c_i \in C$. These user's behaviour features are weighted using various coefficients to indicate their importance (i.e. α_V, α_M, α_T and α_P). These weights are adjustable factors that allow for greater or lesser importance to be placed on each component when calculating the degree of interest based on the system's requirements and user preferences.

  The implicit preference of the user u_x in the each category $c_i \in C$ (i.e. $IP_{u_x}[i]$) is calculated according to the Equation 3.

$$IP_{u_x}[i] = \frac{P_{u_x}(c_i)\times\alpha_P + M_{u_x}(c_i)\times\alpha_M + V_{u_x}(c_i)\times\alpha_V + T_{u_x}(c_i)\times\alpha_T}{P_{u_x}(C)\times\alpha_P + M_{u_x}(C)\times\alpha_M + V_{u_x}(C)\times\alpha_V + T(C)\times\alpha_T} \tag{3}$$

  where $P_{u_x}(c_i)$, $M_{u_x}(c_i)$, $V_{u_x}(c_i)$ and $T_{u_x}(c_i)$ reflect the user's u_x purchases, 3D manipulations, views and teleportations within the product category c_i. And $P_{u_x}(C)$, $M_{u_x}(C)$, $V_{u_x}(C)$ and $T_{u_x}(C)$ reflect the user's total purchases, 3D manipulations, views and teleportations of products in the portal within any of the portal categories.

  To obtain the user category preferences matrix of a user u_x, noted as MP_{u_x}, user's explicit preferences EP_{u_x} and implicit preferences IP_{u_x} are weighted following the Equation 4.

$$MP_{u_x}[i] = \alpha_{IP} \times IP_{u_x}[i] + \alpha_{EP} \times EP_{u_x}[i] \tag{4}$$

  where α_{IP} and α_{EP} are two parameters that allow us to determine the importance of each of the two preferences (i.e. implicit and explicit preferences).

  The matrix capturing the similarity between users according to their preferences matrices MP_{u_x} in the different product categories of C, denoted as MP, is calculated according to the equation 5.

$$MP[u_x, u_y] = \sum_{i=1}^{|C|} |MP_{u_x}[i] - MP_{u_y}[i]| \tag{5}$$

- **User Age (*MA*).** This refers to the similarity matrix that assesses how similar users are based on their age groups. Fuzzy logic is employed to categorize users into age groups following the membership function seen in Figure 1. In this way we transform raw age data into a set of fuzzy values, such as ‘kid’, ‘teenager’, ‘young’, ‘adult’, ‘middle age’, or ‘senior’, taking into account the gradual transitions between categories. The resulting matrix helps to understand how users in similar age groups may share common characteristics, providing valuable insights for user similarity analysis and recommendation systems.

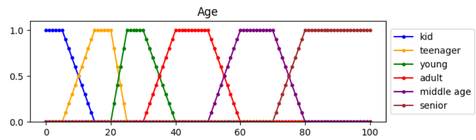

Figure 1: Membership function of variable *age*.

The matrix that captures the similarity between users u_x and u_y according to their fuzzy ages, denoted MA, is calculated according to the equation 6.

$$MA[u_x, u_y] = Sep(age_{u_x}, age_{u_y}) \quad (6)$$

where Sep is the measure of comparison S proposal in (Castro-Schez et al., 2004) and age_{u_x} and age_{u_y} will be values present in the domain of definition of the variable *age*, see Figure 1, representing the fuzzy ages of the user u_x and u_y.

- **User Monetary Spending (*MS*).** This refers to the similarity matrix used to evaluate user spending patterns across different product categories. Using fuzzy logic, users are categorized into spending levels (low, medium and high) within each product category following the membership function seen in Figure 2. The resulting matrix offers a measure of affinity among users based on their purchasing behaviors, enabling a nuanced understanding of shared financial preferences. Fuzzy logic plays a pivotal role in categorizing users into spending levels, taking into account gradual transitions between these categories. This not only reflects the inherent variability in users’ spending habits but also allows for capturing subtle nuances in financial preferences.

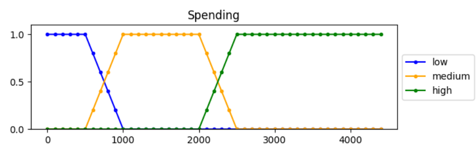

Figure 2: Membership function of variable *spending*.

The matrix capturing the similarity between users according to their monetary spending in each category, denoted as MS, is calculated according to the equation 7.

$$MS[u_x, u_y] = \sum_{i=1}^{|C|} Sep(Spend_{u_x}[i], Spend_{u_y}[i]) \quad (7)$$

where $Spend_{u_z}[i]$ is the fuzzy value taken from the definition domain of the variable *spending* shown in Figure 2, which represents what the user u_z has spent in the category c_i.

These matrices constitute a crucial element of our recommendation system. Following the derivation of these matrices, a composite matrix (M) is computed using equation 8.

$$M[u_x, u_y] = \alpha_{MP} \times MP[u_x, u_y] + \alpha_{MA} \times MA[u_x, u_y] + \alpha_{MS} \times MS[u_x, u_y] \quad (8)$$

Once the weighted matrix M of distances between users is obtained, the fuzzy c-means clustering algorithm is applied. We choose $|C|$ as the number of clusters we want to obtain (i.e. the number of categories that are available on the portal).

The algorithm produces a vector (MC) with dimension $|C|$ that shows the membership degrees of each user for each cluster (i.e. each category). The user’s u_x membership degrees for each cluster i is stored in $MC(u_x)[i]$ and represents the categorization of the user as a user who is interested in the category i. The possibility of belonging partially to several clusters captures the ambiguity inherent in users’ purchase decisions, as well as their implicit and explicit preferences.

Each cluster (i.e. each category) will be represented by its cluster centers.

2.4 Pickup Point

Pickup points are designated physical locations where users can collect their purchased products. Users enjoy the flexibility to choose their preferred pickup point from a selection of pre-designated stores, with the added convenience of selecting an approximate pickup time.

The system stores essential information for each pickup point, including a unique identifier (*id*), the point’s name (*name*), its geographical coordinates (*latitude* and *longitude*) and its credential information, email and password (*email* and *pwd*). Formally pickup points (PP) can be formally defined as:

$$PP = (id, name, latitude, longitude, email, pwd, time) \quad (9)$$

2.5 Leisure Plan

Leisure plans in the portal are crafted to create a unique connection between leisure activities and the individual profiles of users. These plans are dynamically generated based on the preferences and behavior of each user, offering a personalized leisure experience that complements their online purchase. When a user makes a purchase, they receive a leisure plan (LP) comprising customized suggestions for leisure activities (LAs). The LP is defined as a collection of these activities (i.e. $LP = \{LA_x, LA_y, \ldots, LA_k\}$, each chosen to align with the user's unique interests and the timing of the activities (i.e. $LAs \in LP$ are ordered in based on their times (*start* and *end*)).

The concept of leisure plans extends beyond just providing entertainment suggestions. It strategically enhances local cultural and entertainment offerings, with the dual aim of enriching the user's experience and stimulating the local economy. These plans are tied to the user's chosen product pickup point, ensuring convenience and encouraging engagement with nearby leisure activities.

Leisure plans are integral to the user's post-purchase journey on the portal, offering a blend of product collection convenience and personalized leisure recommendations. This approach not only makes the user experience more engaging but also supports local economic development. By connecting users to diverse cultural and leisure activities, the portal facilitates the discovery of new experiences within the city, thus contributing to the diversification and strength of the local economy. This synergy between users and local businesses fosters a mutually beneficial environment, enriching user experiences while sustaining the vitality of local businesses.

3 LEISURE PLAN GENERATOR ALGORITHM

This section introduces a specialized framework tailored explicitly for plan recommendation. The aim is to understand user preferences and provide finely-tuned recommendations, carefully curated around activities, events or experiences.

The leisure plan generator algorithm provides personalized recommendations to users based on the cluster they belong to.

To initiate the process, the first step involves determining the cluster or clusters to which the user belongs. This is achieved by employing Algorithm 1, which evaluates the membership degree (*MC*) to each cluster. It checks whether the maximum *MC* exceeds the threshold α. If not, it verifies whether the difference between these *MC* values is less than another threshold β. If so, the user is associated with multiple clusters; otherwise, the user is assigned to the cluster with the highest membership degree.

Data: membership degrees vector MC, α, β
Result: Relevant category/categories for the user (CAT).
$max\_val = max\{MC[i]\}$
$CAT = \emptyset$;
if $max\_val > \alpha$ **then**
  $CAT = CAT \cup \{i \mid \max_i \{MC[i]\}\}$
else
  for $i = 1$ *to* $|C|$ **do**
    if $|MC[i] - max\_value| < \beta$ **then**
      $CAT = CAT \cup \{i\}$
    end
  end
end
return CAT

Algorithm 1: Dominant cluster algorithm.

Once the dominant categories of the user who has made the purchase have been obtained (i.e. CAT), the algorithm that generates the leisure plan will be executed, taking into account the pick-up point, the date and time at which the user will go to pick it up (Algorithm 2).

The Algorithm 2 employs a multi-faceted filtering process. Firstly, it ensures that the leisure activities align with the user's specified pickup date. Then, it selectively includes activities that fall under the categories represented by the user's dominant preferences (CAT). Next, the algorithm calculates distances between each leisure activity and the designated pickup point. The approach selectively includes only leisure activities that are within a reasonable proximity, ensuring that the calculated distances do not exceed the specified threshold α. This mitigates potential user discomfort associated with distant locations. Finally, any leisure activities that occur before the user-specified pickup time are excluded.

Within the Algorithm 2, *distance* is a function that calculates the distance between the place where the leisure activity takes place and the pickup point. And *arrange* is a function that randomly selects a number of different leisure activities from the list and arranges them according to their start and end times, ensuring that they do not overlap and that there is a margin of time between them to allow for displacement (β).

The implementation of these steps leads to the creation of a customized leisure plan based on the user's preferences, ensuring an engaging and tailored experience.

Data: CAT, α, β and pickup point PP, date and time of pick-up, LLA
Result: Leisure Plan LP.
$LP = LLA$;
for *each* LA_i *in* LP **do**
  if $LA_i.date \neq date$ **then**
    $LP = LP - \{LA_i\}$
  end
end
for *each* LA_i *in* LP **do**
  if $LA_i.category \cap CAT = \emptyset$ **then**
    $LP = LP - \{LA_i\}$
  end
end
for *each* LA_i *in* LP **do**
  if $distance(LA_i, PP) > \alpha$ **then**
    $LP = LP - \{LA_i\}$
  end
end
for *each* LA_i *in* LP **do**
  if $LA_i.start < time$ **then**
    $LP = LP - \{LA_i\}$
  end
end
$LP = arrange(LP, \beta)$
return LP;

Algorithm 2: Leisure Plan Generator Algorithm.

4 ILLUSTRATIVE EXAMPLE OF THE PROPOSED ALGORITHM

In creating the virtual landscape for the VR-ZOCO platform, we strategically chose Ciudad Real as our focus city for a number of compelling reasons. Ciudad Real not only embodies a rich cultural heritage, but also boasts a diverse range of businesses, making it an ideal setting for our empirical study. The city's unique blend of cultural richness and urban vibrancy serves as a canvas for our exploration of the dynamics of leisure links within a virtual realm.

For this specific use case within the VR-ZOCO platform, our focus is narrowed down to 14 key business satellites selected throughout Ciudad Real described in Table 4 and located in Fig. 3. Each location acts as a representative hub, offering unique leisure activity in six different categories C - beauty, culture, home, fashion, sport and technology. We have also included two establishments that are considered restaurants or cafes that belong to multiple categories simultaneously.

We introduce the user X as a representative user, offering an insight into his purchases and interactions within the portal. User X serves as an illustrative case study for our investigation into personalized user experiences. The user X named Ana, a 25-year-old interested in sports and technology, provides a nuanced lens through which to evaluate the efficacy of our system.

After collecting Ana's data, we proceed to construct her user profile using a clustering approach. The obtained results for each cluster are as follows in Table 1.

Table 1: Initial membership degree (MC) results.

Beauty	Culture	Fashion	Home	Sport	Technology
0.112596	0.076077	0.081246	0.075429	0.340955	0.313697

As expected, higher values are observed in clusters associated with sports and technology, accurately reflecting Ana's initial preferences. Following various interactions with products of interest, such as views on sports and technology-related items, as well as 3D manipulations for each, Ana ultimately decides to purchase a technology product. Using the Algorithm 1, Ana has 2 dominant clusters: sports and technology (see Table 1). The product purchase triggers different leisure activities, taking temporal constraints, distance from the pickup point to the satellite business, and user profile into account, the results are then arranged in Table 2. The outcome for the first leisure plan is "Espacio Serendipia" from the technology category.

Table 2: Proposals for the first Leisure Link.

Satellite Business	Leisure Plan	Category
Espacio Serendipia	Machines learning, humans on alert	Technology
Living Room	Math Street Fighter: Maths vs Humans	Technology
Polideportivo Rey Juan Carlos	Provincial Swimming Championship	Sport
Bar Entretapas	-	*
Quijote Arena	Handball Match Caserío CR vs Sinfin	Sport
A Pares	-	*

Subsequently, the generation of the second leisure plan takes place. Here, it's essential to acknowledge that the first plan concludes at 20:00. The results are represented in Table 3. In this case, the distance from the first leisure plan generated, the user profile and temporal constraints are taken into account. As a result, "Bar Entretapas" emerges as the recommended option, providing a holistic and tailored sequence of activities that not only adheres to Ana's preferences but also factors in practical considerations for a seamless and enjoyable experience.

Table 3: Proposals for the second Leisure Link.

Satellite Business	Leisure Plan	Category
Bar Entretapas	-	*
Quijote Arena	Handball Match Caserío CR vs Sinfin	Sport
A Pares	-	*

Ultimately, the leisure plan generated for Ana consists of picking up the purchased product from the

Table 4: Locations and Leisure Proposals.

Place name	Category	Leisure Proposal
Centro Ayurveda Fusionatur	Beauty	Massage Session
Primor	Beauty	Make-up Course
Biblioteca de Ciudad Real	Culture	Videogame Saturday
Auditorio de la Granja	Culture	Concert: Pablo López
Antiguo Casino	Home	Casa y Jardín Expo 2023
Pabellón Ferial	Home	ExpoHogar
Plaza Mayor	Fashion	Fashion Trend Showcase 2023
Moda re- Ciudad Real	Fashion	Charity Clothes Collection
Polideportivo Rey Juan Carlos	Sport	Provincial Swimming Championship
Quijote Arena	Sport	Handball Match Caserío CR vs Sinfin
Espacio Serendipia	Technology	Machines learning, humans on alert
Living Room	Technology	Math Street Fighter: Maths vs Humans
A'Pares	*	-
Entretapas	*	-

Figure 3: Locations of Leisure Proposals.

pickup point "PCBox", followed by a visit to "Espacio Serendipia" for a technology talk. Subsequently, there is the opportunity to unwind and enjoy refreshments at "Bar Entretapas". This carefully curated itinerary is visualized in Figure 4, presenting a seamless sequence of activities tailored to Ana's preferences. Figure 4 serves as a comprehensive representation of the suggested journey, providing a visual guide for Ana to make the most of her personalized and enjoyable experience.

This sequence of activities not only maximizes Ana's satisfaction by aligning with her interests but also promotes the local economy by encouraging participation in nearby events. This personalized recommendation approach, tailored to Ana's preferences and behaviors, underscores our model's capacity to provide unique and relevant experiences for each user.

5 CONCLUSIONS AND FUTURE WORK

In conclusion, this paper extends an innovative architecture that represents a significant advancement in the evolution of e-commerce portals, especially in supporting small and medium-sized enterprises (SMEs). The integration of "satellite businesses" diversifies the traditional product-centric focus of e-commerce, fostering a synergistic relationship between online shopping and physical leisure activities. Users can collect purchases at specific local points, streamlining logistics and helping the environment. This also promotes the generation of personalized "leisure plans" based on the offerings of these satellite businesses.

Figure 4: Representation of Leisure Links.

As a future research effort, enhancing the arrangement function (*arrange*) within Algorithm 2 is proposed. Instead of a random approach, the aim is to develop a more sophisticated method that optimizes the arrangement of leisure activities, accounting for individual preferences, distances between locations, and temporal constraints. This refinement seeks to further enrich the users' experience by providing more personalized leisure recommendations aligned with their specific preferences.

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