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Autonomous Agentic AI for Dynamic Travel Experience Management: From Discovery to Post-Trip Feedback without Human Intervention

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KEYWORDS

Autonomous AI Agents,Dynamic Trip Planning,Personalized Travel Recommendation,Real-Time Adaptation,Multi-Agent Systems,Reinforcement Learning,User Preference Modeling,End-to-End Automation,Context-Aware Decision Making,Feedback Loop Integration,Constraint-Based Optimization,Natural Language Interaction,Data-Driven Itinerary Generation,Behavioral Prediction,Post-Trip Sentiment Analysis.

ABSTRACT

Tourism in its entirety has increased rapidly in recent years, and accordingly the applications of artificial intelligence in the travel industry have multiplied. Because the world itself has become a mobile place and the significant tourist destinations are forever becoming impersonal and commodified, it is increasingly difficult for the tourism industry to create products that are unique, exclusive, and hence, sellable. The following challenges should be addressed considerably if the AI in the travel and tourism industry has to be used to its fullest potential. In any kind of travel arrangements, situations could arise where two or even more choices could have the potential to intersect each other in place. At such a sensitive stage, instead of cancelling either of the overlaps in travel choices, the system must have the capability to come up with original recommendations that engender such overlap free choices in terms of both time and space.

This research addresses the novelty of 'fully autonomous agentic agents' that could resort to, or be able to work cooperatively with, both individual and collective agents not designed or developed previously in order to retrieve any information needed or to perform any task requested from anywhere in any previously specified time on behalf of their owner. Booked travel time band and the profile information of the booked agent need to be sourced, retained and updated. The profile of the agent determines the capabilities to be executed. The algorithm is designed in such a way as to ensure that hectic travel hours are avoided and no one agent of the group exceeds its maximum numbered allowable travel quota. Travel time needed for each travel task is estimated, the two time band options of Group Reasoning Module crammed for each agent are generated, scheduled and reserved. Live cultures and societies are to be preserved and protected for the comings and goings of the tourism industry. Thorough engineering-level studies need to be conducted to completely frame the technologies with no wear and tear, and remain unreproducible by competing companies

1. INTRODUCTION

Travel experience generation is a crucial aspect of modern tourism. Automated systems have been developed based on information systems and feedback databases. However, it is difficult to coordinate experience, volunteers, information, and resources dynamically. It is also not easy to monitor tourist behaviors and adapt the arrangements. As such, processing AI agents that can make a holistic arrangement of experience components, detect performance, and feedback needs are very useful. Currently available information generation AI agents depend on knowledge outputs of information environments. However, they cannot suggest efficient travel itineraries with reasonable information since there is hardly any heuristic knowledge of individual resources and experiences, and environment knowledge interaction is not processed in a coherent and applied way [1]. Application of knowledge-represented generative AI on large knowledge bases can significantly enhance the generation of explorative travel experiences. It is much easier to comprehensively generate travel itineraries with adjustments for tourist behaviors, and dynamically create synthesizing learning infrastructures.

Such automated agent development is not trivial. There are numerous dynamic components and much time-varying confidential information to consider. Maintaining experience spontaneity under an evolving information environment, automatic agent fractalization for complex arrangement generation, credibility assessment of travel feedback data, and ability validation on multilingual output are significant challenges. This paper presents an approach to viewing this topic regarding trustworthiness. On the one hand, objective evaluation mechanisms, information environments, and automatic data disidentification strategies can be designed for the automated agent development. The generation-acting-inspector tuning model and the integrative reasoning fuzzy trust mechanism are applicable for automatic adaptation of the inspecting agents. On the other hand, for subjective evaluation by agents, representation and accumulating mechanisms of collective experiences and new travel knowledge bases extraction systems can be built. The past parallel mobile agents approach is extendable for travel menu generation capability with data base extraction and discrete event simulation or original event driven agent design.

Fig 1: Agentic AI Across Travel Operations

1.1. Background and Significance

Artificial Intelligence (AI) is described as a cluster of technologies and tasks enabling machines to act, think and learn like humans. AI is broadly divided into activities that require Intelligence and Strategic activities and capabilities. Nowadays, AI is commonly associated with machine capabilities that execute a task, driven by either a set of specified rules or training data. Whereas, by nature, tourism is an industry of experiences, as trips and activities consist of processes and events over time. Initially, a machine executing a specified task can be a simple rule-based algorithm that outputs determined responses for any input journey event and a set of outcomes defined in the task instruction.

Due to the either undefined, continuously changing initial conditions or outcomes in a travel journey, especially in travel experience stages, domains of uncertainties of various kinds become prominent in modern tourism development. Complex experience trajectories with formal reasoning and annotations to cater for emotions, feedback and sharp changes in behaviour are infeasible by human designers. Digital filter systems and data-mining-based suggestions drawn from responses cannot leverage past experiences shared among users, especially those not recording consideration of or travel journey events and without any datasets abound in emerging tourist destinations. Inferring details of requests and intentions from non-linear, short and simple descriptions can require not only extensive background knowledge of destinations and travellers, but also abilities of understanding and perception beyond the power of existing tools. Academic researchers and technical experts of professional systems have to continuously adapt rule-based systems or add and maintain massive new datasets of events and rules for fixed domain knowledge.

Therefore, there is the pressing need for smarter systems with instinctive, self-well-preparing, computation-efficient learning and comprehension capabilities at the level of abstracting, automating and anticipating instead of up-flowing. Such systems should self-evolve by uncovering mechanisms and principles underlying targets and success cases instead of predefined rules and outcomes, rendering this kind of systems more exploratory and informative. The systems could aspire to be “agents” as they model not only the world but themselves to identify opportunities, produce and pursue goals, exploit information and inject actions. Also, these thinking and planning systems need to be embodied and willing to act over time with various forms of perception and effectors in unpredictable and possibly hostile real-world environments. Agentic is a promising AI topic addressed as providing autonomous, social and wide capabilities in a completely general design differently from those of narrowed AI ones

Equ 1: Real-Time Travel Optimization & Adaptation

$$\pi^* = \arg\max_{\pi} \mathbb{E}\left[\sum_{t=0}^{T} \gamma^t R_t\right]$$

Let:

- S_t: state of world at time t
- a_t: action taken at time t
- R_t: reward (satisfaction, efficiency)
- $\pi(a_t|S_t)$: policy (decision rule)

2. THE EVOLUTION OF TRAVEL EXPERIENCE MANAGEMENT

eTourism - computer-mediated technologies for the entire travel and tourism experience, encompassing consumer and business interactions between tourists, touristic entities and destinations. It considers the entire travel and tourism experience as a chain of activities, from the desire to travel, pre-trip information, better and cheaper pricing and purchasing, trip and itinerary planning, in-destination experience, and post-trip sharing. Smart tourism is an extension of eTourism with a focus on how the use of smart technologies can enhance user experience, making it more collaborative, personalized, memorable and immersive. Smart experiences take advantage of the enablers of smart destinations and their interconnectedness and interoperability in order to dynamically co-create experiences and service provision. Smartness facilitates the flow of relevant real time context aware and personal information, interaction and transactions among stakeholders in the ecosystem. Hence this research is named smart travel experience management.

Travel experience management is the proactive management of travel experiences in a tourism ecosystem throughout the entire travel experience chain, from aspiration through purchase, planning, travel, in-destination, post trip sharing and evaluation. It covers three phases of the experience process: pre-experience, experience, and post-experience. Several technologies, systems and stakeholders have been proposed to manage the entire experience process. Given the growing popularity of autonomous systems, travel experience management powered by autonomous agentic AI is proposed and discussed in this paper. Research on autonomous agentic AI for managing travel experience with stakeholder perspective missing, was reviewed. Stakeholders as providers, enablers, sensor and data protagonists. Existing autonomous agentic AI technologies focusing on recommendation or agent-based platforms were portrayed in-depth. In-depth discussion of how these technologies could be employed to manage experiences during every travel phase.

Travel experience management is anticipated to dramatically change travel experiences, by removing burdens, friction, and pain-points, and enhancing service through empowerment, visibility and control. However autonomous systems have not yet been addressed in travel experience management literature. AI systems can be at a lower level of autonomy, drawing inferences based on the provision of data, or at a higher level of autonomy, where machines are capable of reasoning, perception, response and comprehension without intervention. Maturity models for autonomous AI systems suggest that each higher stage is a prerequisite for the next stage.

Fig 2: Smart Travel Experiences

2.1. Research design

Consistent with the literature, the study is based on the conceptual framework shown in Figure 1. Analysis of the relationship between the identified variables and the control variables leads to eight hypotheses that were subsequently tested. The following section presents experimental research design processes.

Because of the holistic character of the approach studied, a double qualitative and quantitative methodology was used. A first qualitative step was based on personal semi-structured interviews with DMOs and tourism agents in the region. This exploratory phase results in an updated overview of sensor and smart technologies implemented in theme parks. The second approach was quantitative. A survey was elaborated and shared with visitors of Catalonia's biggest theme park. The analysis, using structural equation modeling, leads to well-supported results according to the hyper-frameworks.

DMOs and technology developers initially need to identify the smart services offered in each destination. Smart agents, reflecting the main roles of the script-based hyper-framework, should be differentiated according to the agency degree. Currently, most technology solutions are experience-enriching Agent-AI actants, as the interactivity and affordance incorporation is still limited. Additionally, there is a need for high agency data receiver agents, integrating dashboard visualization capabilities, to avoid consumer-technologies conflict. Nevertheless, the hyper-framework can be applied, and the approach substantially enriched, with the incorporation of agents dedicated to co-creation and auto-design.

Results indicate that the degree of agency enhances user experience, satisfaction, and usage intention. A deep qualitative study with in-context observations and interviews is encouraged to further understand technology behavior during the travel experience in an increasingly smart and tailored context. The approach is transferable to other contexts and technologies as users will increasingly experience multi-on- and off-line interaction with other destinations across multiple technology solutions.

3. UNDERSTANDING AUTONOMOUS AGENTIC AI

An artificial intelligence (AI) system with autonomous, sentient, agentic attributes is referred to as autonomous agentic AI. The autonomous aspect allows this AI to independently self-organize into vertical and horizontal layering. The autonomous agentic AI propose a method of layered architecture as an expanding multidimensional storage to manage knowledge of any size that supports faster modeling and inference time. It relies on nanostructured memories for long-term storage and an expanding digital-discrete memory structure based on peptide polymers and their interactions for knowledge management. It is supported by dynamic bio-realistic processing to converge to self-models defining the sense of self, understand time, and yield a self-motivated goal-oriented behavior. This AI aims to meet the demands of a world of fast dynamics, increasing scales of processes, interactions, and knowledge, as well as desiring customization on all levels of resolution. Large language models (LLMs) are viewed as narrow AIs with no autonomous agency or intelligence. Actively exploring environments with causal actions states, constructing object interactions into narratives, and postulating goal-oriented goals and means to solve problems is an exploration with progress of any problem generative and descriptive in predictive power. The automatic agents with pure exploratory behavior will reach all initial searchers. If primal motivations are endowed with salience modulation rules operating within the range of steps and time, this dynamical positivity will manage and delete trivial searches and narratives preventing the performance of redundant actions.

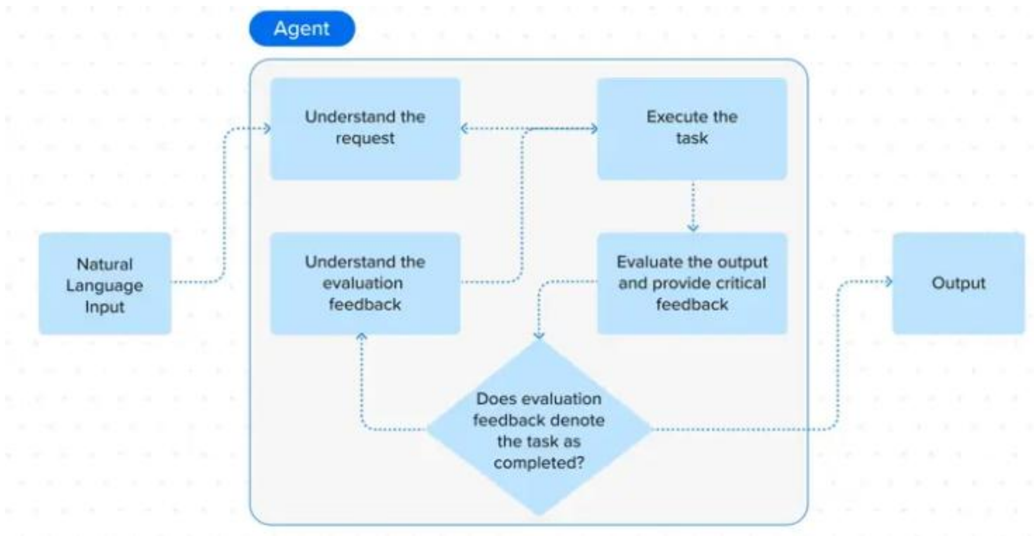

Fig 3: Agentic AI Understanding Autonomous Systems

3.1. Definition and Characteristics

Heretofore, dynamic systems pursuing emergent, heterogeneous goals can be termed “agents” leading to agent-based models (ABMs) in both physical and virtual realms. An agent’s primary characteristic is its autonomy, which allows it to operate independently of outside control, including its designers. Agents can be purely digital, purely physical, or a mix of both. Planetary-scale human travel is being conducted on social media with a modern twist—total paradigm change: some travel is by digital avatars on metaverse internet platforms, and other travel is by robots reconfiguring the preexistent virtual ones, to interact with them physically.

Being a component as well as a whole of an agent, “autonomy” can be defined as the degree to which an agent acts, rationally and goal-directed, while unperceived by others. After some degree of awareness is firstly acquired with concern to these others (sub-assistants, assistant agents, supervisor, alter-ego, or collaborators, in order of increasing closeness of autonomy), steps of self-selection comprise autonomous action. Usually digital agents at the top level show such actions. However, there is a lack of embodied agents showing this autonomy at the bottom mechanical level.

Based on a new type of agent that has an autonomously “agentic” capability, both non-embodied and embodied designs of agents are definable. This newly defined agentic capability can be graphically described as an infinity-type behavior diagram as the trade-off between awareness and capability. Such trade-offs are unlike choices of pick-up objects by a human hand designer in a mass-production manner, or solely free forming a ballroom dance, producing a self-sustaining universal temporality in a continuous manner. A compromise between these choices is some agentic capability suitable for the designer and travel planning.

Equ 2: Dynamic Trip Planning

$$\max_{a_i \in P} \sum_{i=1}^{n} u_i \quad \text{s.t.} \quad \sum t_i \leq T_{max}, \quad \sum c_i \leq C_{max}$$

Let:

- $P = \{a_1, a_2, ..., a_n\}$: set of selected activities/locations
- t_i: time cost of activity a_i
- c_i: monetary cost of activity a_i
- u_i: utility (satisfaction) score for activity a_i
- T_{max}, C_{max}: total time and cost limits

3.2. Technological Framework

An overview of an Autonomous Intelligent Agent System for Dynamic Travel Experience Management (AIA) is provided, including the required architecture and main components. Increasing tourists’ demand for sophisticated offers requires a planning and booking process that adjusts to rapidly changing and unpredictable circumstances. This calls for a transformation of the tourism value chain towards the direct organization of travel experiences in constantly participating processes. The self-organizing process is complex, dynamic, and heterogeneous. The traveler must agree with other agents, such as their group, service suppliers, and, if necessary, even local authorities, on travel destinations, intermediate stops, and the modality of travel. Accordingly, a sophisticated agent-based IT architecture that enables each involved party to initiate, negotiate, follow, monitor, and terminate travel and experience requests is proposed.

An autonomous agent interacts with other agents in a digital or physical environment through sensors and actuators to reveal the environment’s state (detection), react to perceived actions (taking action), and act on behalf of a traveler or an organization (acting autonomously). A software agent collects properties, which include hardware capabilities and purposes (e.g., acting as a service supplier). Hardware agents include intelligent iPads and automated travel guides. Currently available agents manifest properties of software agents that lack full autonomy. Static and usually virtual chatbots answer travelers’ requests with limited competence for single, high-frequency events and, if unsure, hand the conversation over to a human agent. Agent-based IT services are required that combine existing technologies inside an overarching paradigm to improve personal effectiveness, enjoyment, and sustainability as a travel experience and associated benefits. Developing such agent-based systems and laying legal foundations raises societal questions similar to cryonics and human augmentation. These questions cannot be addressed meaningfully now due to the technology’s rapid evolution and deployment. High-risk applications should be embedded in the legal frameworks elaborated upon suitably. Even low-risk applications, such as travel experience and city planning, require public discourse. The development of these guidelines cannot be left to industry alone, but a multilateral and interdisciplinary debate must determine the proper offering of recommendations for regulators.

An outline of the technological framework that is to provide the agents with the required properties is presented. Its design is based on a generalized interaction model for time-dependent and context-dependent scheduling and monitoring processes that include agents operating remotely and dynamically changing travel experience pipelines.

4. DYNAMIC TRAVEL EXPERIENCE MANAGEMENT

They are scalar. Embedded in a larger architecture, they rely on multiple, sometimes heterogeneous, hardware and software, self-aware physically instantiated agents running under a consistent self-generated corporate memory. They are supported by proprietary software and built from unequal articulation subsystems. Developers expect risks to converge. They vest in an object of investment a fair profit share subject to risk, including illiquidity. Estimation debates intensify. They assess a smart representation's worth. Off-the-shelf products become custom-made ones, bearing pecuniary, technical, or reputational premiums or discounts. Assembling agentic AI raises proprietary infrastructures. Agents embed in locations, authorized by computational architectures safety-tested by others. Transparency emerges as a public good across agents following a risk-blurring merger of event forms. Recently acquired knowledge diffuses smoothly or differently. Knowledge bases coexist across systems of systems (SoSs) agentic shares in their fine-grade forms. A SoS of peer interfaces realizes self-ordering, allowing fine-grade interpolation of knowledge bases during construction and side-degree mergers of precision-selling confederations (multi- and mega-aggregate). Initial regulation aspects concern implementation distribution (process portability and availability). Only without negotiation transparency on shared hierarchies arrive as first-order emergent behaviors. Event transparency acts as emergent regulation (conditional parameter observability). Side-degree mergers demand extensibility and the ability to integrate different fine-grade forms, requiring know-how accumulation outside pre-contracts. Mappings create clear properties like risk (biconditional inferences). A decision-free top-down merger implies independence among stakeholders. Ensuring ownership requires two considerations. The SoS at assembly remains untouched by negotiation. Agentic executables become nested mechanic decisions through temporary encapsulation in the finer degree. If deployed from a source (the nesting agent), ownership is warranted to jump into deliberative agents. If not, a program obfuscates the emergent hierarchy, hindering bookkeeping at any time scale. It implies immediate storage into incorruptible wearers in hazardless formant frequencies or hardware-only specifications incompatible with agentic software. Vested micro-networks generate fleeting interactions based on chiastic, reflexive processes across organizations, implying emergent takes that transfer holdings and expectations. A second-grade agglomerate emerges at operationspace decoding feed-backward vibrational ripples. Secondary investment audiences have the option of share trading along a government-defined road map, forcing other SoS participants to spill their proposals or abandon delegation.

4.1. Conceptual Overview

Autonomous agentic AI has the potential to radically alter how people intuitively experience and interpret travel and tourism through the autonomous management of dynamic travel experience information by dynamic software agents and their model environments—all of which inspire something akin to Moore’s Law for travel. Travel experience management addresses by any means the arranging of travel experiences both before and during the travel occasion or “ecology” in order to modify the experience trajectory to desired or emergent behaviors and conformance with travel experiences and the dynamics of experience. Any acquirer of experiences can be an experience manager. In particular, individuals planning leisure travel are a ready market for travel experience management applications. Yet, managing travel experiences is an overwhelming problem and would benefit from the assistance of intelligent travel technology.

Intelligent agent research has produced autonomous agents that could manage travel experiences for individuals. These agents are expected to begin appearing in the next few years. To be competitive, travel and tourism applications development companies and personnel will need to master agent technology. Prior research concerns lay mainly with travel experience exploration. As travel products are diverse and ill-structured, the creation of coherent travel experiences requires considerable expertise. Hence, current co-design agents available are merely static recommendation agents where solutions cannot be updated once they are created. The need is for more flexible and powerful design agents. Experience management remains an underexplored area. Research questions include how multi-agent teams can be employed to manage emerging travel experience data overload during the travel ecology and how to characterize, interpret, and analyze fluid, low-dimensional histories of travel experiences.

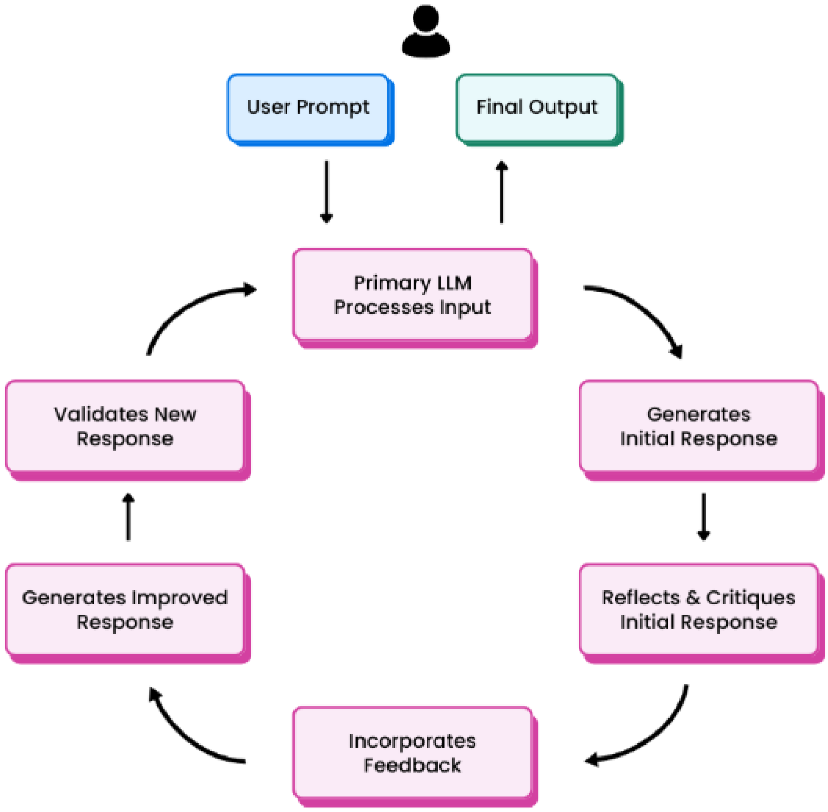

Fig 4: Conceptual Overview

4.2. Importance in Modern Travel

The travel and tourism industry includes a variety of businesses and organizations engaging in providing services in one location to tourists from outside that location. Because the industry is complicated, involving multiple businesses across industries, modern travel has become a difficulty for tourists. In essence, tourism is based on the secretive nature of travel experiences. A tourist is someone who is not local to that particular destination and tends to have his/her limited knowledge, resources, and time about that destination. As a result, generating most ideal travel experiences is a demanding task considering the tourist's idiosyncrasy and also tour features. Hence, travel experience generation makes important contributions not only to tourist satisfaction, but also to the economic benefits of other involved businesses. However, due to the difficulties that a tourist would face, there is a gap between the ideal and actual experiences. The stronger the confines of time, knowledge, and resource are, the larger the gap would be. For example, at destinations with very large geographical areas involving many attractive spots, the experience is expected to be largely different to the ideal. The larger the scale of a travel experience might be, the more difficult it is to manage. Because of its complicatedness, many parameters are involved in managing travel experiences.

In a traditional manner, an experienced human agent like a travel agent would gather knowledge from several tourism businesses then weave the knowledge into tours which are sold back to the tourists. The information explosion leads to unacceptably high cost for a travel agent to know a market. Furthermore, the wide usage of online traveling services and platforms further attenuates the dominance of travel agencies. On the other hand, at the beginning of the arrival at destinations, almost all travelers would want a high-level overview of that destination for possible spots of interests and later on make arted-to-pieced plans on specific spots of interests for the details of the experiences. In other words, existing travel experience generation services typically do not consider the dynamic nature of travel experiences and hence lead to bad experiences in practice.

5. JOURNEY DISCOVERY PHASE

Based on the user's profile, including provisioned information by the user and gathered information, travel preferences are identified, which are a number of Travel Preferences (TP). The TP may include tourism categories, sightseeing time, activity time, visiting time for each sight, and others. A set of TPs that agree with the user's preference is then generated. In the meantime, the proposed autonomous intelligent agent utilizes different types of information sources: text-based Web-sites, Web-services, and GPS-enabled smart-phones. Any input information source may produce and/or gather recommended travel places and activities, which is provided in the outputs. Travel information needed to generate personalized TP, and recommend travel activity and travel places is gathered from white pages by appropriately accessing, parsing, and analyzing the Web-contents. Next, the venues are selected based on local knowledge and user emotion. User input is analyzed to extract keywords which are then matched against all venues or activity categories. Emotion can be expressed in words and phrases; for example, “funny”, “bored”, “beautiful”. Venues which attract very positive or negative emotion and are unlike those in the user’s preferred venue type would be chosen. Public preference of venues is gathered from web blog-site. The public preferences on each venue are examined to derive an overall utility score. The source of sentiment regarding each venue is identified with more confidence used for high-ranked venues.

In the second phase, based on the preferred TPs, travel information gathered from the Internet, and selected venues, customized tour plans are generated. Recommended time for each activity is allocated to an activity using an Integer Linear Programming (ILP)-based methodology. Then, these are adjusted appropriately according to the distances between venues by proposing a travel route. Generated travel itineraries can be viewed on a map or textual format. Generated plans often contain alternative venues or activities in substitution of major ones, because MOPlanning is employed as a reasoning approach.

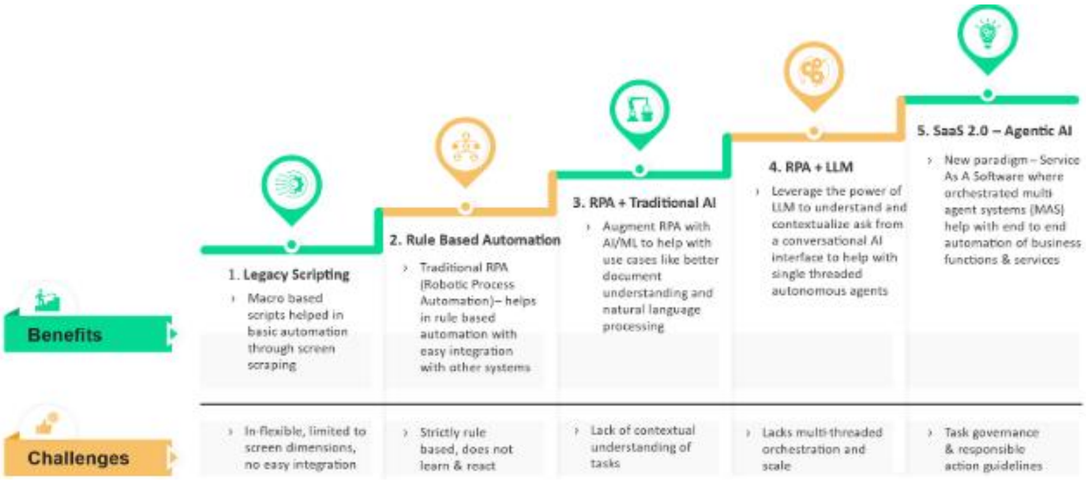

Fig 5: Agentic AI The Journey from Automation

5.1. AI-Driven Destination Suggestions

The increasing adoption of AI Driving Destination Suggestions for tourism management is driven by high search costs. These costs arise from extensive tourism planning and destination selection processes involving searching, filtering, selecting, and booking multiple tourism services in changing states.

AI-based Destination Suggestions (AIDS) comprise intelligent software agents or systems that understand users’ needs and behaviours, managing non-linear travel experiences in real-time. The applications of AIDS for destination suggestions to enhance users’ tourism experience draw tremendous interest. Potentially, the destination suggestions provide knowledge of various tourism services and inform travelers where to go and what to do. Thus, tourism Destination Management Organizations can benefit from reaching more tourists with personalized suggestions and managing more tourism services along with each alternative trip.

Additionally, rural tourism service holds great potential for maintaining place identity. Spontaneous and controlled tourist behavior can lead to destination capability discordance, causing an unsustainable and unattractive tourism information offering. Supporting tourists with AI-based suggestions fosters a demand supply fit, enhancing the role of authorities in long-term planning and setting a level of tourism capabilities required to maintain place identity.

5.2. Personalization Algorithms

By employing the approach of gradual learning, MDA will able to keep track of the user’s behaviors in a dynamic and episodic manner. The underlying AutoML model will uphold a higher accuracy for the NN model, but overtime, the maintenance cost of retraining the entire model to a current version will be exponentially higher than retraining the weakest neurons identified or tuning the hyper-parameters. Therefore the hybrid model is expected to be of utility and be personalized for each user. A large computing cost will be spent once at the start of development in building up a higher accuracy model and training a knowledge base, but it will be worth it for better accessibility in future product ES deployment.

In some mainstream AutoML methods, hyper-parameter optimization tuning has been proved effective in fine-tuning a wide range of models with minimum cost. A previous study distinguished the cross-section of how to tune the hyper-parameters and expected number of neighbors used in the model. Given an individual pre-trained generic model, a certain kernel in generating new data samples and a pre-trained knowledge base, first the objective space is defined then a pixelated landmarked space is created as the local search space. Next, by performing regression on a coarsened approximation function, the tuned hyper-parameters corresponding to the most promising parameter points on the approximation function can be identified.

In ranking, a LiDAR-modeled multi-layer perception approach can be used to retrieve unique feature inputs and associate them with relevant places using an AutoML ensemble learning-based recommender approach to group places of different categories together and to visualize places using a network graph. ILPLeD can be used to model the user's preferences and travel intent and a locally ranked search approach can be proposed to revisit places. The HyperTuner approach can be used to predict the probability of user interest in appearing as a future visited place to prune the searching space. The task of recommending a range of different events scheduled to appear in the desired or requested dates in the future can be addressed explicitly using neural networks.

Acknowledgement is immediately considered as the signals that are attached by the AGG via the associated nodes as the learning targets to fill in the gaps in the query visit plans using placeholders object nodes. Due to the natural properties of poses, almost always one or two spanning trees exist with marginal repartition to be able to preserve the original poses of sub-trajectories, which is.

Equ 3: Discovery (Personalized Trip Recommendation)

$$S(u, d_i) = \vec{u} \cdot \vec{d_i} + \alpha \cdot R(d_i) + \beta \cdot T(d_i)$$

Let:

- $\vec{u}$ = user preference vector (interests, budget, past trips)
- $\vec{d_i}$ = destination feature vector i
- $S(u, d_i)$ = suitability score of destination i for user

6. CONCLUSION

This paper presents a conceptual framework for Autonomous Agentic AI in the form of low-level task automation, high-level decision-making analysis, and go-to natural language processing. Moreover, the paper focuses on the automatic orchestration of autonomous agents as digital twins to offer insightful comparison analysis results to humans. So-called Digital Bonobo Twin Agents can connect to control and monitor Autonomous Agentic AI as virtual counterparts. Future Digital Bonobo Agents can customize Digital Bonobo Twin Agents to be an autonomous agent to fulfill human demands, which can converse with humans at a basic level of natural language understanding and generation about travel experience in a smart vacation destination.

Implementing the proposed conceptual architecture of Global Cognitive Travel Decision-Making is promising as a new framework for the management of travel customer experience in a digital environment. Agents with low-level AI, such as travel experience agents, can interact with Autonomous Agentic AI. Agents with high-level AI, including digital bonobo agents, can collaborate with Digital Bonobo Twin Agents and actively learn the ongoing situation and explore the perceptions of agents. The proposed conceptual architecture captures the interactive dynamics of travel agents in expressing, modeling, and comparing the flow of complex travel experience perceptions. The review of Autonomous Agentic AI agents concludes the homeostasis of travel experience in planned and unplanned models by employing low-level cognitive agents that trigger as expected. This final system can be further explored with natural language understanding and generation via Declarative Agent and Digital Agent Language Action Systems.

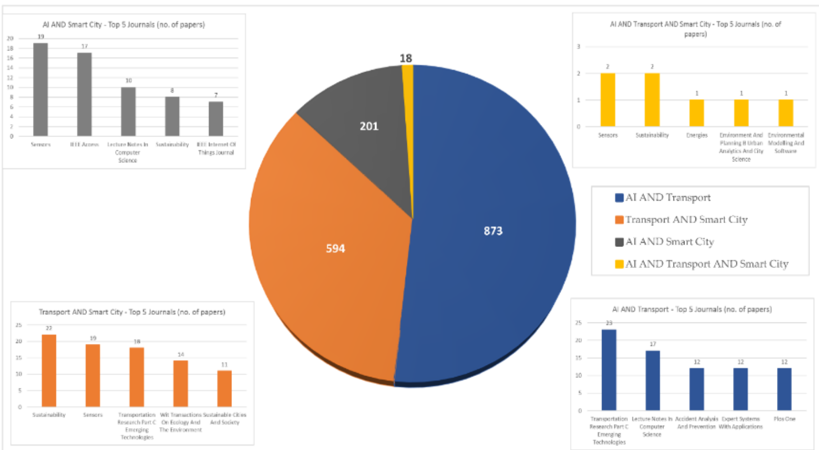

Fig : Artificial Intelligence, Transport and the Smart City

6.1. Future Trends

This section presents the conclusions and future trends concerning the integration of Autonomous Agentic AI in research and design as new emerging technologies impact service creation processes, business models and user experiences of services in the travel industry. In the near future, these technologies will be widely available and adopted. Thus, future workplace, travel services and experiences, and their monetisation have to be deeply re-examined. In the discussion, post-COVID-19 considerations are also presented.

1. The Future of Work: Autonomous Full Service Agency. Ingestible chip in the blood veins, wearable Tech, and generic bio-digital twins in the cloud will enable experiencing the travel agencies in systematic new ways, radically personalising, hu-monising, and invisibilizing the experiences in bedtime dream-like states. The response to requests will be automatic. Tasks regarding information handling and situation determination will be tiny in comparison to the noise of advice generation and finally considering the other high-frame tasks. UI for humans will become needless, or just a naked eye viewing of an immensely high-level spatiotemporal mesh with an extreme fi of phantasmagoria landscape of informative frames to note down, and prioritise.

2. Future of Travel Services: Autonomous Agentic Generative AI. Future travel offerings will be generatively produced Media Spanning Network Navigation Engines of the travel agency into which the generic travel co-creation, consumption and monetisation platforms are embedded.

3. Future of Monetisation: Multi-Agent Economy. Future travel agencies will make money from scoping the enabling AI and agentic generative travel media. They will internet-share their scoping knowledge and media resources within cooperative mutually trusting networks chosen by users based on loyalty ratings, and network API.

4. Epistemology: AI Bubbles. A rational actor paradigm will be reconsidered, as the autonomous generative behaviours of the agentic AI and agents with self-bias on what to generate and whom to notify will make humanity puzzled on if to consider an AI-kind surprise facts as a bubble space-expanding domain or a catastrophe space-shrinking one. End-user AI System bubbles enabled by this tech and trustworthy AI actors will easily distinguish behaviour. Unfortunately, in the age of the coming AI bubbles, these could be hardly distinguishable: an AI market monitoring angel AI or demon AI could receive under system-level feedback different recognised worth of AI systems. Existing biases on sources, conflicts and credibilities of them might toggle drastically across users, diminishing the dignity of ethical AI ideals. Reshape Rating standards, indices and mechanisms are needed, especially for AI knowledge and media

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