Personalized Recommender System for Improving Urban Exploration and Experience Documentation of International Students

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Abstract: International students face significant integration challenges in new urban environments. Documenting their experiences is crucial for reflection and adaptation; however, linguistic and cultural barriers often hinder effective documentation. This study introduces a personalized recommender system designed to facilitate this process, enhancing social engagement. The system provides targeted prompts that guide students towards richer, more reflective annotations. Utilizing a mixed-methods approach—quantitative analysis of user interactions and qualitative feedback—we evaluated its impact. Our analysis demonstrates that the recommender system substantially enriches student documentation, fostering deeper connections with new surroundings, enhancing textual and emotional expression, and promoting diverse and reflective perspectives. These findings highlight the system's potential to accelerate international student adaptation and offer insights for future technologies aimed at improving their global integration and well-being.

1 INTRODUCTION

International students often encounter significant challenges adapting to new cultural and urban environments, which can adversely impact their academic performance and well-being (Patel et al., 2024). These challenges, encompassing cultural differences, unfamiliar urban landscapes, and language barriers, can exacerbate isolation and hinder their sense of belonging (Gutema et al., 2024). While social networks and local support systems are critical for academic success (Zhou et al., 2008), along with practical skills such as navigating public transportation and accessing essential services, traditional support mechanisms often fail to provide the continuous, personalized assistance that international students require (Martirosyan et al., 2019). Digital tools, conversely, offer scalable solutions by providing real-time, tailored support through mobile applications and social media.

The MOBILES application (Lefevre et al., 2024) is designed to enrich the social and spatial experiences of international students by facilitating the documentation and reflection of their urban interactions. While the application offers a platform for recording experiences, it falls short in guiding students toward meaningful reflection. Without structured support, deep engagement remains elusive, as effective documentation is key to fostering thoughtful interactions, enhancing language skills, and supporting integration. However, linguistic barriers and unfamiliar cultural norms often hinder students from creating insightful records of their experiences. This study is therefore designed to answer two critical research questions: (1) *How can digital tools be optimized to assist international students in producing insightful documentation of their urban experiences?* and (2) *How do personalized recommendations affect the quality of annotations made by students during urban exploration?*

This article contributes by integrating a personalized recommender system into the MOBILES application and empirically evaluating its effectiveness. The system provides tailored prompts to encourage reflective, detailed documentation, addressing linguistic and contextual barriers and fostering deeper connections to the local environment. Through analysis of student interactions and feedback via questionnaires, this study provides valuable insights into the role of recommender systems in improving documentation practices and supporting student integration.

The remainder of this paper begins with a literature review, followed by a description of the MOBILES app and its recommendation model, the study and results, and a discussion of findings.

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2 LITERATURE REVIEW

2.1 International Student Integration

The integration of international students into host cities involves cultural adaptation, social integration, and navigating unfamiliar urban environments (Gutema et al., 2024). These challenges are central to developing intercultural competence and personal growth (Deardorff, 2006), but cultural adaptation often disrupts academic performance and well-being, with students facing isolation and frustration due to unfamiliar norms and academic expectations (Zhou et al., 2008). This initial disorientation complicates adjustment, especially in the early stages. The COVID-19 pandemic further exacerbated these challenges by increasing isolation through online learning and travel restrictions (Gutema et al., 2024). While universities have introduced support programs like language assistance and peer mentorship, these efforts often fail to meet the diverse needs of students (Martirosyan et al., 2019), highlighting the need for more targeted approaches.

Digital tools present promising solutions to support international students. For instance, mobile apps offering city guides, language translation, and cultural insights help students navigate their new environments (Kukulska-Hulme, 2020). These apps improve language skills, boost confidence in daily interactions, and foster social connections, reducing isolation (Loewen et al., 2020; Sun, 2023). However, many existing tools focus solely on specific tasks, such as orientation or language learning (Huynh and Tran, 2023). There is a clear need for culturally responsive platforms, tailored to diverse backgrounds and learning styles, to better address integration challenges and promote academic success.

2.2 Recommender Systems in Education

Recommender Systems (RS) suggest items or content by analyzing user behavior, preferences, and interactions. Leveraging advanced algorithms, they deliver personalized recommendations that enhance experiences across various domains, including e-commerce, entertainment, healthcare, and education. In the educational context, RS support personalized learning by recommending tailored resources, courses, and pathways, leading to improved academic performance, motivation, and outcomes (Silva et al., 2022). Key approaches include collaborative filtering (drawing on preferences of similar users), content-based filtering (suggesting similar items), and hybrid methods.

(a) Homepage. (b) An annotation.

Figure 1: MOBILES main interface.

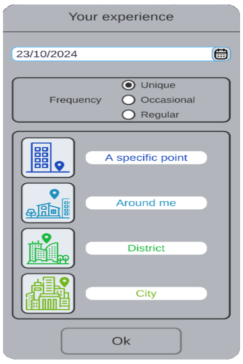
Knowledge-based systems rely on domain-specific criteria, while context-aware systems incorporate factors like time, location, and activity to provide highly relevant recommendations.

Beyond academics, RS contribute to social integration and adaptation in new environments. Personalized recommendations not only support academic pursuits but also enhance the social aspects of student life (Urdaneta-Ponte et al., 2021). For instance, context-aware systems can suggest local events, study spots, and social gatherings, facilitating integration (Sassi et al., 2017). They further enrich experience documentation by encouraging reflective entries that foster deeper cultural engagement (Gumbheer et al., 2022). To aid international students in adapting to new environments, we leverage context-aware systems to enhance urban experience documentation through personalized prompts and location-based recommendations.

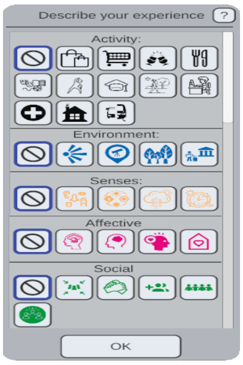
3 MOBILES RECOMMENDER SYSTEM

3.1 MOBILES Application Overview

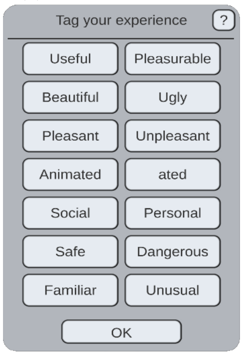
MOBILES is an application designed to facilitate urban exploration, experience documentation, and social interaction for international students in France. It enables users to plan tours, document activities, and share experiences, fostering cultural engagement. The main interface (Figure 1) provides access to key features, including location discovery and a map visualizing user-generated content. This map highlights geographic points of interest and student annotations, enhancing navigation and contextualizing urban experiences. Routes are presented as a sequential narrative of urban explorations, enriching the user's journey.



(a) Context information.



(b) Icons selection.



(c) Tags selection.

(d) Emoticon selection.

Figure 2: Key elements in the annotation creation process (the interface text is translated into English).

Annotations are multi-faceted records capturing the breadth of student experiences. The annotation creation process (Figure 2) enables students to capture key contextual details, including the temporal and spatial scope of their observations (Figure 2a). This scope can be categorized as *unique*, *occasional*, or *regular*, and can range from *a specific point* to *city-wide*. Each annotation includes a text field for narrative descriptions, with the option to add photos and select from a range of categorized icons (Figure 2b). These icons are color-coded into thematic categories: *Activity*, *Environment*, *Sensory*, *Social*, and *Affective*. Additional expressive features include tags (Figure 2c) and emoticons (Figure 2d). Annotations can be shared publicly, restricted to specific groups, or kept private, and can be edited at any time.

In addition to individual annotations, MOBILES enables the creation of routes, which record the overall path of urban explorations. Routes can be generated via *automatic GPS tracking*, *manual route mapping*, or *retrospective journey sequencing* of individual annotations. The application allows linking annotations to specific tours and repositioning on the map, promoting adaptability. User interaction is also facilitated through comment and reaction features.

The application backend integrates the *Kernel for Trace-Based Systems* (kTBS) (Settouti et al., 2009), a RESTful service managing timestamped event traces. Each user interaction is captured as a time-stamped trace specifying the event type and associated data. This trace data supports detailed behavioral analysis and informs application improvement.

Additionally, the application features modules designed to enhance user experience, including a *Favorite Manager* for organizing content and a *Notification Center* for real-time updates, ensuring continuous engagement.

3.2 Recommender System

To improve international students' use of the application, we have developed a personalized recommender system (Sadallah and Lefevre, 2024) that enhances their documentation practices. The system provides context-aware prompts and suggestions to encourage reflective engagement with their surroundings, while also helping students overcome linguistic and contextual challenges.

The application relies on interaction logs captured through the integrated kTBS module, which records timestamped user actions and geospatial data. The recommender system processes these logs to generate personalized recommendations using three key methods: (1) *Collaborative filtering*: by analyzing interaction patterns, the system recommends content favored by similar users, fostering a sense of shared experience; (2) *Content-based filtering*: this method matches content attributes with user profiles to provide suggestions aligned with individual interests; and (3) *Geographical context*: leveraging location data, the system delivers recommendations tailored to the user's current environment. The combination of these techniques ensures that recommendations are personalized, contextually relevant, and adaptive to the user's needs.

3.3 Recommendation Strategies

The recommendation engine employs five research-backed strategies to provide personalized, contextually relevant, and comprehensive guidance to students during their experience documentation.

Stimulating Activity. Active engagement in documentation is critical for capturing a broad range of experiences. Higher engagement yields richer content for reflection and analysis. We define the *Activity*

Engagement (ActEng) metric as:

$$ActEng = \sum_{i=1}^{n} (C_i + M_i + T_i) \tag{1}$$

where C_i denotes the number of annotations created, M_i the number of annotations modified, and T_i the number of tours edited. When $ActEng$ falls below a predetermined threshold, the system prompts users to increase documentation activity.

Promoting Textual Narrative Richness. Detailed textual descriptions are essential for promoting deeper reflection. Personalized prompts enhance contribution quality and encourage critical thinking (Mueller and Richardson, 2022). *Textual Mass (TM)* quantifies textual quality:

$$TM = \frac{1}{n} \sum_{i=1}^{n} \left(\frac{LV_i + LD_i}{2} \right) \tag{2}$$

where LV_i is the Lexical Volume (total word count in annotation i), and LD_i is the Lexical Diversity (ratio of unique to total words in annotation i). The system prompts for more detailed text when a user's TM falls below the average.

Encouraging Sensitive Expression. Expressing emotions through annotations enhances the documentation process, adding authenticity and offering insights into students' experiences. Highlighting these aspects is essential for creating detailed, meaningful annotations, given the importance of emotional communication (De Stefani and De Marco, 2019). The *Sensitive Rate (SensR)* metric is defined as:

$$SensR = w \cdot AAR + (1 - w) \cdot AIR \tag{3}$$

where AAR is the *Affective Annotation Rate* (proportion of annotations with affective icons), AIR is the *Affective Icon Rate* (ratio of affective to total icons), and w is a weight parameter (default: 0.7). The system prompts for increased emotional expression when $SensR$ falls below a threshold.

Increasing Graphic Usage. Incorporating visual elements enhances annotation quality, improving clarity and engagement (Guo et al., 2020). The *Graphic Expression (GrEx)* metric is defined as:

$$GrEx = \frac{N_{graphics}}{N_{total}} \tag{4}$$

where $N_{graphics}$ is the number of annotations with graphics, and N_{total} is the total number of annotations. Users receive prompts to incorporate more visuals when $GrEx$ is low.

Diversifying Icon Use. Diverse icon use enriches visual storytelling, making documentation more accessible and engaging while overcoming language barriers (Santos, 2020). The *Icon Diversity (IcD)* metric is:

$$IcD = \alpha \cdot ANI + \beta \cdot ANIT \tag{5}$$

where ANI is the average number of icons per annotation and $ANIT$ is the average number of icon types per annotation. The system also analyzes icon type distribution using:

$$IcD_{type} = \frac{Icons_{type}}{Total_{icons}} \tag{6}$$

where $Icons_{type}$ is the number of icons of a specific type, and $Total_{icons}$ is the total number of icons in an annotation. Recommendations are generated based on the least diverse icon types when IcD falls below a specific threshold.

3.4 System Architecture

The MOBILES recommender system is an independent module within the application's architecture, designed to generate and deliver personalized recommendations. It automatically captures real-time user interactions through a tracking module, which logs the data on a kTBS server for behavioral insights. The application database stores essential information such as user profiles, annotations, trajectories, and preferences, crucial for personalizing recommendations.

The system uses a multi-phase data pipeline to collect, process, and analyze user data, ensuring adaptive, data-driven recommendations. Data from both the kTBS server (which logs events) and the application database are continuously gathered. The data is then preprocessed to remove duplicates, handle missing values, and standardize formats. Behavioral metrics are calculated to generate actionable insights for personalized recommendations.

Recommendation generation involves deriving these insights and formulating personalized suggestions based on strategic metrics. Each recommendation consists of a *Prompt*, which encourages actions based on past behavior, and a *Suggestion*, which provides contextual elements, such as examples from peers, to support these actions.

To optimize engagement, recommendations are tailored to the user's history, with delivery timing adjusted for maximum effectiveness. These recommendations are delivered via push notifications and are accessible in the notification center. A feedback loop tracks user interactions, logging responses on the kTBS server for continuous system refinement.

This modular design ensures that the system is scalable and maintainable, enabling seamless updates to individual components without disrupting service. It also ensures continuous access to up-to-date data, enhancing the overall user experience.

4 STUDY

4.1 Study Design and Participants

This study investigated the impact of personalized recommendations on international students' documentation practices within the MOBILES application for urban exploration. Specifically, it focused on how recommendations influenced annotation quality and engagement, contributing to social integration in an urban context. A mixed-methods approach was employed to assess the recommender system's effectiveness and understand participants' experiences.

International students from universities in Lyon, France, were recruited via on-campus postings and university mailing lists. A diverse group of 31 students participated, comprising 15 males and 16 females, with a median age of 24 (range: 19-43). The cohort included 9 first-year and 22 mid-year students (14 undergraduates, 8 postgraduates). Geographically, 18 participants were from Africa, 4 from the Americas, 4 from Asia, and 2 from Europe.

The study, conducted from March 25 to May 2, 2024, comprised three phases. In the initial phase, participants provided informed consent, were introduced to the research project, and installed the application. During the second phase, participants independently explored Lyon, documenting their experiences using the app. Regular personalized recommendations were delivered via in-app notifications. The application tracked user interactions with consent, providing detailed behavioral data in a real-world context. In the final phase, participant feedback was collected using an online questionnaire and semi-structured focus groups.

4.2 Procedure and Instruments

This study used a mixed-methods approach to evaluate the recommender system, analyzing the evolution of recommendation metrics alongside a focus group discussion and a structured questionnaire.

4.2.1 Impact of Recommendation Strategies

To evaluate the recommendation strategies, the evolution of key metrics was tracked over time, including *Activity Engagement (ActEng)*, *Textual Mass (TM)*, *Sensitive Rate (SensR)*, *Graphic Expression (GrEx)*, and *Icon Diversity (IcD)*. This longitudinal tracking was used to identify improvements or regressions attributable to the system's suggestions. For example, an increase in *TM* would suggest that textual prompts were effective in encouraging richer and more diverse contributions, and changes in *SensR* would reflect the effectiveness of emotional prompts in enhancing the emotional richness of annotations.

4.2.2 Focus Group Session

At the end of the study, a focus group session was held to discuss participant experiences with the application, specifically focusing on feedback regarding the recommender system. This provided insights into the relevance and usefulness of the personalized recommendations.

4.2.3 Structured Questionnaire

Participants completed an online questionnaire, which included a section on the recommender system with two parts. The first featured closed-ended questions, where participants rated their agreement with statements on a 5-point Likert scale (*1 = strongly disagree*, *5 = strongly agree*):

1. *Relevance to personal interests:* The recommendations were relevant to my personal interests and preferences.
2. *Variety of recommendations:* The recommendations offered a diverse range of places and events to explore.
3. *Facilitation of discovery:* The recommendations facilitated my discovery of new and relevant places or events.
4. *Quality of annotations:* I am satisfied with the quality of the annotations suggested for documenting my experiences.
5. *Clarity of recommendation logic:* I clearly understand the reasoning behind the recommendations, based on my history and preferences.
6. *Encouragement to engage:* The recommendations motivated me to engage more with the application and use it regularly.
7. *Enhancement of experience:* Overall, the recommendation module significantly enhances my experience.

The second part included open-ended questions to capture deeper insights, providing context for the ratings and addressing areas not captured by the closed-ended questions. These questions focused on:

1. *Positive Impact:* Recommendations that positively influenced experiences and the reasons for their impact.
2. *Personalization:* Suggestions for better tailoring the recommendations to individual needs.
3. *Overall Impact:* Assessments of the recommendations' influence on app usage and exploration.

4.3 Results

The study results focus on two areas: the impact of the recommendation strategy and participants' direct feedback. Combining quantitative metrics with qualitative insights provides a comprehensive evaluation of the recommender system's effectiveness in enhancing urban documentation.

4.3.1 Impact of Recommendation Strategies

The system's impact on user documentation was evaluated using metric evolution analysis and focus group insights. Metrics for recommendation strategies were analyzed weekly during the active usage phase. To assess the strategies' impact over time, each metric was examined. Table 1 shows average evolution rates, means, medians, and the number of recommendations sent and used. Figure 3 illustrates the distribution of these evolution rates by metric.

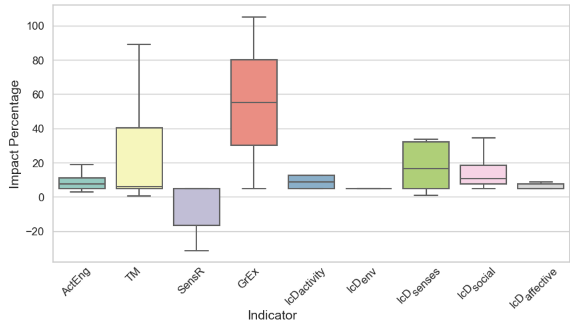


Figure 3: Impact distribution by recommendation type.

Table 1: Impact statistics by recommendation type.

Recommendation metrics	*Median*	*Mean*	#
Activity (*ActEng*)	7.5%	10.1%	24
Textual Mass (*TM*)	5.9%	21%	20
Sensitive Express. (*SensR*)	5%	-5.9%	21
Graphical Express. (*GrEx*)	55%	55%	5
Activity Icons $IcD_{activity}$	8.9%	8.9%	5
Env. Icons (IcD_{env})	5%	30%	7
Senses Icons (IcD_{senses})	16.5%	24.3%	9
Social Icons (IcD_{social})	10.8%	15.3%	6
Affective Icons (IcD_{affect})	5%	19.6%	8

Stimulating Activity. Personalized recommendations significantly impacted documentation activity. The *Activity Engagement (ActEng)* metric, tracking annotation and tour creation/editing, showed a weekly average increase of 10.11% (median: 7.50%) following 24 recommendations. This indicates increased user activity due to relevant prompts. Participants noted that tailored recommendations served as both reminders and encouragement, particularly during initial adoption. One participant stated, "*The notifications were not just reminders, but also encouragements that kept me engaged, especially in the beginning*," highlighting the role of personalization in driving early engagement.

Promoting Rich Textual Narratives. The *Textual Mass (TM)* metric, measuring annotation textual richness, showed a median weekly increase of 5.86% and an average rise of 21% after 20 personalized recommendations. This growth indicates more elaborate and diverse user entries. Participants noted that personalized prompts encouraged reflection, citing example entries as inspiration. One participant stated, "*The annotation suggestions that accompanied the recommendations introduced me to well-written entries that served as inspiration, even though I don't feel I have the language skills to write at that level*," highlighting the system's role in inspiring richer annotations despite varying language confidence.

Encouraging Sensitive Expression. The *Sensitive Rate (SensR)* metric, measuring emotional expression through icons, tags, and emoticons, showed a median weekly increase of 5% and a mean decrease of -5.96% after 21 recommendations. This indicates varied responses to emotional prompts. Some participants valued the emotional prompts, stating, "*The icons helped me share emotions I often find hard to put into words*." Others found them irrelevant or prescriptive, commenting, "*The prompts felt artificial and pushed me to express myself in ways that don't match how I naturally describe my experiences*." This highlights the need for more tailored emotional support.

Increasing Graphic Usage. The *Graphic Expression (GrEx)* metric, assessing visual inclusion in annotations, showed a 55% average weekly increase after five personalized recommendations. Despite the strong increase, only five recommendations were sent as participants already frequently used images. Prompts served as valuable reminders, with one participant noting, "*Including photos made my entries come to life, and the prompts reminded me to capture moments I would have missed*." This suggests the system effectively encouraged mindful visual documentation despite the already high baseline.

Diversifying Icon Use. Personalized recommendations significantly diversified icon usage in annotations. Activity icons increased by 8.85%, while environmental icons showed a median increase of 5% (mean: 30%). Sensory icons exhibited a median increase of 16.54% (mean: 24.27%), social icons increased by 10.83% (median), and affective icons showed a median increase of 5% (mean: 19.95%). This underscores a positive influence on icon diversity and annotation richness. Participants noted that these recommendations helped them explore the variety of icons, with one participant stating, "*These recommendations improved my annotations and allowed me to clearly tell my experiences*." This demonstrates how recommendations encouraged enriched documentation by promoting broader icon usage.

4.3.2 Participants' Feedback

The closed-ended questionnaire, with responses from 25 participants, assessed key aspects of the recommender system using a Likert scale (1 = *strongly disagree* to 5 = *strongly agree*). Table 2 summarizes satisfaction regarding recommendation relevance, variety, applicability, and perceived clarity.

Table 2: Summary of closed-ended questionnaire results (from 25 participants).

Question	*Median, Mean(SD)*
Relevance to Interests	3.5 – 3.50 (1.21)
Recommendations Variety	4 – 3.66 (0.89)
Facilitation of Discovery	4 – 3.69 (0.92)
Relevance of Suggestions	4 – 3.84 (1.04)
Clarity of Recommendation	3 – 3.38 (1.02)
Encouragement to Engage	4 – 3.61 (1.10)
Enhancement of Experience	4 – 3.73 (1.96)

Participants rated recommendation relevance as moderate (median/mean: 3.5), with varied satisfaction, reflecting mixed perceptions of the system's ability to enhance documentation. Satisfaction with recommendation variety was higher (median: 4, mean: 3.66), though some lower ratings indicated a need for greater diversity. Discovery facilitation was also valued (median: 4, mean: 3.69), but lower ratings indicated some students may find recommendations less useful for already familiar locations. The relevance of suggestions also received positive, albeit varied, ratings (median: 4, mean: 3.84). Understanding of the recommendation logic was rated moderately (median: 3, mean: 3.38), suggesting a need for greater transparency. Encouragement to engage with the app was moderate as well (median: 3, mean: 3.61), highlighting a need for more personalized prompts. Finally, the user experience was perceived as enhanced (median: 3, mean: 3.73), but neutral responses among several students suggest the need for further refinements.

Qualitative data from the open-ended questions revealed that participants valued the suggested annotations and their personalization. However, some noted the need for more transparent recommendation logic and improved tailoring to individual preferences. Overall, these findings indicate that while the recommender system is effective in various aspects, enhancing personalization and addressing user experience variability could significantly improve overall satisfaction and engagement.

5 DISCUSSION & CONCLUSION

This study explored the impact of personalized recommendations on international students' urban experience documentation. Our findings reveal their potential to deepen annotations and increase engagement, though their effectiveness varies depending on individual users and contexts, highlighting the complexity of experiential documentation.

Personalized prompts often led to more detailed and thoughtful reflections, but responses varied widely. This variation underscores the need for a recommender system that can continuously adapt to different emotional styles and offer nuanced support. For some, these prompts sparked deeper emotional expression, while others found them less relevant, reinforcing the importance of personalized, context-sensitive recommendations.

The study also confirmed the value of diverse expressive tools. Participants appreciated the variety of icons, and visual prompts were effective in encouraging the capture of key moments, emphasizing the role of multimodal features in meaningful documentation.

While user feedback indicated general satisfaction with the relevance and diversity of recommendations, it also highlighted the challenge of catering to individual preferences. For greater user trust and engagement, more transparency in the recommendation logic is needed. Additionally, the system's ability to help users explore unfamiliar areas was highly appreciated, reinforcing its potential to foster a sense of belonging and support integration.

Despite these insights, the study is subject to certain limitations. The relatively small sample size and heterogeneity of responses pertaining to emotional expression limit the generalizability of the findings. Furthermore, the study did not assess the long-term impact of these recommendations, thereby identifying a critical area for future research.

Future research should expand beyond annotation quality to include urban discovery, social integration, and language acquisition. Adaptive learning algorithms to further enhance personalization should also be explored. Finally, examining long-term effects on social integration and well-being is paramount.

This study underscores the significant role of recommender systems in helping international students document, reflect on, and engage with their experiences in host cities. By addressing their specific challenges, the system fosters self-reflection, enriches local engagement, and supports integration through tailored suggestions. These systems not only enhance students' ability to capture their experiences but also contribute to their personal growth and sense of belonging. Ultimately, this research demonstrates the potential of adaptive, personalized technologies to create more inclusive and engaging urban experiences for diverse global communities.

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