parc pesquisa em arquitetura e construção
research in architecture and construction
ISSN 1980-6809 | https://doi.org/10.20396/parc.v16i00.8675731

Innovations for urban management: strategic alignment and knowledge management in a technological ecosystem in Curitiba

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Abstract

This study explores the influence of knowledge management and technical training on organizational capacity for technological alignment, particularly within the innovative context of Curitiba. Aiming to fill gaps in understanding how these factors interact in technological ecosystems, Mixed Linear Models were utilized to analyze responses from 128 professionals, focusing on their experiences with BIM and GIS technologies. The methodology involved comprehensive statistical analysis, ensuring the study's replicability. The results indicate a significant positive correlation between knowledge management and technical training (KMTT) and organizational capacity for technological alignment in innovation ecosystems (OCTAIE), demonstrating that each increment in KMTT corresponds to an improvement in OCTAIE. The study also reveals that experience with BIM and GIS technologies and the intensity of their use significantly modulate this capacity. It is concluded that knowledge management and technical training are critical in fostering effective technological integration strategies. However, the specificity of the Curitiba context suggests caution in generalizing the findings, highlighting the need for future research in various technological ecosystems.

Keywords: urban management, technological integration, organizational alignment, knowledge management, technical training.

Inovações para a gestão urbana: alinhamento estratégico e gestão do conhecimento em um ecossistema tecnológico em Curitiba

Resumo

Este estudo explora a influência da gestão do conhecimento e da capacitação técnica na capacidade organizacional para o alinhamento tecnológico, particularmente no contexto inovador de Curitiba. Visando preencher lacunas no entendimento de como esses fatores interagem em ecossistemas tecnológicos, utilizaram-se Modelos Lineares Mistos para analisar respostas de 128 profissionais, enfocando suas experiências com as tecnologias BIM e GIS. A metodologia envolveu uma análise estatística abrangente, garantindo a replicabilidade do estudo. Os resultados apontam uma correlação positiva significativa entre a capacidade de gestão do conhecimento e capacitação técnica (CGCCT) e a capacidade organizacional para alinhamento tecnológico em ecossistemas de inovação (COATEI), demonstrando que cada incremento em CGCCT corresponde a uma melhoria em COATEI. O estudo também revela que a experiência com as tecnologias BIM e GIS e a intensidade de uso modulam significativamente essa capacidade. Conclui-se que a gestão do conhecimento e a capacitação técnica desempenham um papel crítico no fomento de estratégias eficazes de integração tecnológica. Contudo, a especificidade do contexto de Curitiba sugere cautela na generalização dos achados, evidenciando a necessidade de pesquisas futuras em diversos ecossistemas tecnológicos.

Palavras-chaves: gestão urbana, integração tecnológica, alinhamento organizacional, gestão do conhecimento, capacitação técnica.

Funding: Coordenação de Aperfeiçoamento de Pessoal de Nível Superior.
Conflicts of interest: The authors certify that they have no commercial or associative interest that represents a conflict of interest in relation to the manuscript.
Ethical approval: Not applicable.
Availability of data and material: Not applicable.
History: submitted on 02.04.2024, approved on 05.27.2024, published on 01.27.2027
Responsible Editors: Maria Fernanda Oliveira, Sidney Piochi Bernardini, Felipe Corres Melachos, Regina Coeli Ruschel

1. Introduction

In an era of accelerated urbanization, cities face complex challenges that demand innovative and integrated solutions (Ding; Lai; Wang, 2012; Badran, 2023). In this context, Information and Communication Technologies (ICTs) have emerged as catalysts in transforming urban management, promoting efficiency, sustainability, and quality of life (Rezende; Procopiuck, 2018). The advent of advanced systems, such as City Information Modeling (CIM), marks a significant evolution in how cities are planned, constructed, and managed based on technological foundations (Sacks *et al.*, 2018; Gil, 2020a; Pereira; Procopiuck, 2022b). These technologies have enhanced decision-making and the delivery of urban services while facilitating interactions among citizens, government, and the private sector, thereby creating a new dynamic in the urban ecosystem (Albino; Berardi; Dangelico, 2015; Margherita *et al.*, 2023). They open up unprecedented urban management and planning possibilities, providing abundant data and technical tools to support comprehensive data analysis (Batty, 2019; Duarte; DeSouza, 2020).

Integrating Building Information Modeling (BIM) with Geographic Information Systems (GIS) is fundamental for implementing CIM (Xu *et al.*, 2014; Sun *et al.*, 2020; Pereira *et al.*, 2021). BIM provides a detailed representation of buildings' physical and functional characteristics, while GIS offers a comprehensive spatial perspective for broader urban environment analyses (Gil, 2020b). This synergy between BIM and GIS has improved resource management and urban planning, revolutionizing how cities are understood and administered (Pereira; Prokopiuk, 2022). Thus, advancing towards the fusion of these technologies in developing CIM systems inaugurates a new era for integrated understanding of urban environments, considered complex innovation ecosystems (Yigitcanlar, 2009; Bevilacqua; Pizzimenti; Ou, 2023).

However, the evolution of GIS and BIM technologies, and by extension, CIM, does not occur in isolation; it is intrinsically linked to the self-reinforcing environment resulting from the interaction between market strategies and government policies (Amorim, 2015; Bevilacqua; Pizzimenti; Ou, 2023). This environment is characterized by a dynamic interplay of reciprocal influences among technological innovation, regulations, and market demands, creating an ecosystem conducive to technological advancement (Mazzucato; Robinson, 2018; Badran, 2023). In this regard, the processes of technological integration pose significant challenges to the ecosystem, such as internally integrating tools within technologies for the management and operation of simulated objects (Borrelli; Scheer, 2022). Within the context of organizational institutionalism, organizations are understood as active entities within a complex technological ecosystem, influenced by external elements such as market dynamics and government policies, while also playing an active role in shaping this ecosystem with their resources and competencies (Edquist; Hommen, 1999; Phillips; Lawrence; Hardy, 2000; Pereira; Procopiuck, 2022a). The interaction among government policies, market needs, and technological innovation fostered by organizations and professionals exemplifies how this ecosystem can drive the development and implementation of CIM. A virtual city model such as CIM, in turn, is the result of applied knowledge and semantic enrichment (Billen *et al.*, 2014), reinforcing the need for collective and integrated expertise aimed at improving understanding, communication, and collaboration among stakeholders, which is already inherent in urban planning practice (Ketzler *et al.*, 2020).

In this context of GIS and BIM technology evolution, this study investigates the impact of knowledge management and technical training on the organizational capacity for technological alignment in urban development environments. The central hypothesis is that knowledge management and technical training significantly impact the organizational capacity for technological alignment (Chan; Chow, 2007; El-Diraby, 2009; Baud *et al.*, 2014). Specifically, it is anticipated that each increment in knowledge management and technical training capacity (KMTTC) is positively correlated with improvements in organizational capacity for technological alignment in innovation ecosystems (OCTAEI), even considering the intrinsic variability of organizational groups (Azhar, 2011; Mulas; Minges; Applebaum, 2015; Golini *et al.*, 2018). Additionally, it is suggested that professional groups with Experience in GIS and BIM (EXPGB) and the Intensity of Use of these Technologies (IUTGB) by these groups influence both the initial level and the evolution of OCTAEI. This implies that groups with different levels of EXPGB and IUTGB will present varied trajectories in OCTAEI. Thus, OCTAEI varies among groups, influenced by factors specific to each set of professionals, reflecting the complexity of organizational structures and the dynamics of technological capacities in technological development ecosystems (Alharbi *et al.*, 2022; Pereira; Procopiuck, 2022b). To test this hypothesis, Mixed Linear Models will be used, providing a detailed analysis of the relative impact of knowledge management and technical training, as well as the experience and intensity of use of BIM and GIS, on technological integration strategies and technological alignment in organizations situated in complex urban management contexts, such as innovation ecosystems.

2. Theoretical foundation

The theoretical evolution concerning the trajectory of technological innovation in urban systems (Esparza; Krmenec, 2000; McGranahan *et al.*, 2005; McNeill, 2016) underscores the growing need to understand the complex dynamics of sociotechnical transitions in urban ecosystems (Edwards, 2003; Silva; Procopiuck, 2019; Moura; Procopiuck, 2020). This dynamic involves the operational modes of various open and closed organizational forms (Geels, 2006; Yigitcanlar, 2009; Bevilacqua; Pizzimenti; Ou, 2023) and different professional profiles (Pompili, 1992; Yigitcanlar; Velibeyoglu; Baum, 2008; Portmann; Finger, 2016). Initially, the concept of the urban ecosystem was employed to describe the interaction between living organisms and their environments. However, this concept has evolved to incorporate the complex structures of cities, including information technology infrastructure and the built environment, resulting from the actions of various organizations and the application of diverse, aligned technologies (Park, 2014). In response to urban challenges, the concept of the "smart city" has emerged, based on using internalized technologies in cities to optimize the benefits of urbanization, address its challenges, and promote environmental sustainability and human development (MacPhee, 2002; Abreu; Marchiori, 2023; Rodrigues; Ferreira; Ferreira, 2023). A broad set of indicators and variables is essential for evaluating and analyzing the different transition phases of these technological ecosystems, which function as macro units of analysis in specific contexts (Bevilacqua; Pizzimenti; Ou, 2023). However, previous research has presented significant limitations in identifying and defining evaluation criteria and analyzing the cause-and-effect relationships between these criteria (Margherita *et al.*, 2023).

Given this, a coherent and connected set of dependent and independent variables should be formed to contribute to the dynamic development of urban technological ecosystems. A starting point in this set is knowledge management and technical training, which are elements used to ensure the efficient use of these technologies (Chan; Chow, 2007; El-Diraby, 2009; Baud *et al.*, 2014). These variables are intrinsically linked to the dimension of professional profiles and their experience in the organizational market, which have been essential indicators to demonstrate technological maturity and readiness to adopt new tools in different contexts (Azhar, 2011; Mulas; Minges; Applebaum, 2015; Golini *et al.*, 2018). Integrating these dimensions can help understand how organizations can evolve and adapt in technologically advanced environments, reflecting a comprehensive understanding of the variables influencing growth and innovation in complex urban ecosystems.

The mobilization of dynamic capabilities (Teece; Pisano; Shuen, 1997; Pisano; Teece, 2007) has shown promising results in cities such as Milan, Barcelona, and Munich, where adopting management strategies, effective leadership, and dedicated units are fundamental for implementing smart city initiatives. These strategies reflect the traditions and specificities of each city, highlighting that there are many approaches to smart urban development. For example, Barcelona's strong technological tradition facilitated a smooth transition from e-government to a smart city strategy, particularly focusing on improving residents' quality of life. In contrast, Milan and Munich aimed to address particular urban challenges, such as social issues and energy inefficiency (Gasco-Hernandez *et al.*, 2022). This diversity of approaches underscores the importance of adapting smart city strategies to specific local conditions, leveraging available capacities and resources to meet each urban context's needs.

Knowledge management and technical training are processes through which organizations create, share, and utilize knowledge to develop and implement new technologies in innovation ecosystems (Chan; Chow, 2007; El-Diraby, 2009). In the organizational environment, knowledge can be acquired, created, discovered, collected, validated, organized, categorized, stored, and distributed for practical application (Tidd; Bessant, 2009; Baud *et al.*, 2014). Organizations' and technical professionals' reliance on knowledge management is evident, as it is a critical tool, whereby its management involves the capacity to transform research results into applied policies and practices.

In this context, it has been fundamental to distinguish between knowledge management and knowledge engineering. Knowledge management defines the organizational structure, allocates personnel, and monitors activities, while knowledge engineering deals with technical aspects, such as tools for acquiring and representing knowledge. In this interaction, broad technological systems are critical in coordinating the various processes integrating organizational and technological capitals in broad geospatial contexts, mitigating physical and personal limitations (Schwartz, 2006). These processes include creating, sharing, and using knowledge to enhance local government competence, grounding urban planning in deep and integrated knowledge from citizens across different societal sectors. This concept is particularly applicable in urban contexts through the digitization and spatialization of information (Baud *et al.*, 2014). Thus, the distinction between knowledge management and knowledge engineering has been relevant in technological innovation processes in urban environments, where the interaction between organizational and technical aspects drives the development and application of intelligent solutions to urban challenges.

Finally, in incorporating BIM-GIS and CIM in organizations, strategies and technological alignment, grounded in internalized knowledge bases, emerge as high convergence points (Pereira; Prokopiuk, 2024). These strategies include evaluating technological internalization readiness, employee training, process and organizational structure adaptation, and alignment with public and private markets (Pereira; Procopiuck, 2022b). Effective BIM-GIS integration demands a technological alignment involving strategic interactions among business processes, organizational culture, and local cultures (Alharbi *et al.*, 2022), highlighting the importance of strategies aimed at development and transition in the architecture, engineering, and construction industries. This alignment, systematically and intentionally driven by organizations, is highly relevant for successfully implementing innovative technologies, requiring an approach beyond mere technological adoption, integrating technical, organizational, and cultural considerations to promote a locally adjusted transition towards more advanced practices in urban environments.

Strategies aimed at innovation with BIM, GIS, and CIM technologies encompass aspects, such as development management, operational and maintenance plan, and highly complex evaluations (Wang; Pan; Luo, 2019). In addition to the three-dimensional geometries of traditional models, these technologies involve other dimensional units, such as costs, time, sustainability indicators, and the management of simulated objects (Charef; Alaka; Emmitt, 2018), making their integration a fundamental technical and strategic challenge. This issue involves sharing information and cost data (Smith, 2014) and interacting among organizations operating in peculiar political and market contexts (Pereira; Procopiuck, 2022b).

In summary, current theoretical-conceptual advances have emphasized the complexity and interconnection between organizational, technological, and environmental variables to institutionalize urban innovation ecosystems. It highlights the need for a multidimensional approach incorporating aspects, such as knowledge management, technical training, and the modus operandi of innovative professional communities, underscoring that adaptation and innovation are continuous processes in urban environments. Based on these theoretical considerations, two critical variables can be defined, which will be empirically explored through a research methodology. They are shown in Chart 1. This methodology aims to quantitatively evaluate these variables and their interrelationships in the specific context of Curitiba. It provides an in-depth understanding of how these factors intertwine and influence the dynamics of urban innovation ecosystems.

Chart 1 - Fixed effects variable and dependent variable

Variable	Definition
Knowledge Management and Technical Training (KMTT)	It encompasses the processes through which organizations generate, disseminate, and apply knowledge, along with the technical training of their members, aiming at developing and implementing innovative technologies in innovation ecosystems (Chan; Chow, 2007; El-Diraby, 2009).
Organizational Capacity for Technological Alignment in Innovation Ecosystems (OCTAIE)	The ability to develop and implement strategies that integrate and align emerging technologies, such as BIM-GIS and CIM, with the objectives and processes that depend on internal competencies and resources, as well

	as those shared among organizations within a specific innovation ecosystem (Baud *et al.*, 2014; Wang; Pan; Luo, 2019; Alharbi *et al.*, 2022).

Source: the authors.

3. Methodology

The Mixed Linear Model (MLM) approach was adopted to evaluate the influence of knowledge management and technical training on adopting strategies and technological alignment of organizations within an innovation ecosystem. This method is particularly suitable for analyzing data with hierarchical or grouped structures, as it can handle variability within and between subjects (Heck; Thomas, 2020). This allows for a more precise analysis of fixed and random effects, crucial for understanding the complex and multidimensional dynamics of organizations operating in technologically advanced urban contexts.

This model can be conceptualized as follows:

$$OCTAIE_{ij} = \gamma_{oo} + \gamma_{10}.\ KMTTij + u_{oj} + u_{1j}\ .\ KMTT_{ij} + \varepsilon_{ij}.$$

In this formulation, the response variable $OCTAIE_{ij}$ represents the organizational capacity for strategic technological alignment (OCTAIE), which is modeled as a function of a set of predictor variables and random effects that capture the inherent variation in grouped data.

The global intercept γ_{oo} is the estimated mean organizational capacity for strategic technological alignment when knowledge management and technical training (KMTT) is zero. The coefficient γ_{10} represents the linear effect of the continuous variable KMTT on the dependent variable OCTAIE, indicating the expected increase or decrease in OCTAIE for each unit increase in KMTT.

Finally, the terms u_{oj} and $u_{1j} \cdot KMTT_{ij}$ represent the random intercept and slope effects associated with group j. These terms allow both the initial level (u_{oj}) and the rate of change (u_{1j}) in OCTAIE to vary from one group to another, reflecting the heterogeneity among groups in terms of experience with BIM and GIS (EXPGB) and the intensity of use of these technologies (IUTGB). The error term ε_{ij} captures the residual variability not explained by the model within the groups.

This model captures heterogeneity within groups (intra-group) and between groups (inter-group), reflecting the complexity of organizational structures and the dynamics of technological capacities in technological development ecosystems. Including random terms for experience with BIM and GIS (EXPGB) and the intensity of use of these technologies (IUTGB) acknowledges that the capacity for technological alignment can be influenced by factors that vary significantly among different groups of professionals, depending on their experiences and levels of use of BIM and GIS.

The model specification was subjected to a series of checks and quality evaluations. Model convergence was confirmed to ensure the reliability of parameter estimates. To assess its adequacy, measures such as the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) were used to compare different models and select the best-fitting one. Model assumption verification included inspecting residuals to check for normality, homogeneity of variance, and lack of autocorrelation, with residual plots examined to identify possible deviations from these assumptions. Sensitivity tests were conducted by removing and adding terms to observe the impact on parameter estimates. However, interaction terms were not included to assess their influence on model convergence and interpretation. Specific diagnostics were performed to evaluate multicollinearity among predictor variables, ensuring that high correlations did not compromise coefficient estimation. The external validity of the results was considered, given the complexity of the phenomenon situated within a broad technological ecosystem for the development of GIS-BIM technologies aimed at CIM.

Analyses were conducted using the statistical software SPSS (IBM, 2015) and Jasp (The Jasp Team, 2023). The Restricted Maximum Likelihood (REML) method was chosen for parameter estimation to obtain variance component estimates, an essential choice due to the model's structural complexity. Results regarding effect estimates, standard errors, confidence intervals, and p-values were presented.

The sample size was determined using a 95% confidence level, based on a finite population of 190 individuals, to ensure representativeness and statistical precision. A proportion of 0.5 was estimated for the parameter of interest, reflecting a balanced distribution of the investigated characteristics. From these parameters, a confidence interval of approximately 4.98% was calculated, resulting in an upper limit of 54.981% and a lower limit of 45.019%. The standard error associated with the proportion estimate was 2.541%. The relative standard error was calculated at 5.08%, reflecting adequate precision for the research objectives (ABS, 2024). Based on these criteria, the sample size required for the study was 128 participants. Responses were obtained through an online questionnaire, with a scale from zero (disagreement) to ten (agreement), without identifying respondents, with informed consent, and following all applicable ethical guidelines. This quantitative approach allowed a detailed assessment of participants' perceptions and opinions about the variables, contextualizing them within the GIS, BIM, and CIM technologies innovation ecosystem.

The sample size was adequate for mixed-effects models, especially compared to the estimated parameters totaling 9 degrees of freedom (West; Welch; Galecki, 2022). Only two levels in each grouping factor may limit within-group variation and, consequently, the ability to capture all heterogeneity. However, the definition of these two grouping factor levels was based on relevant theoretical and practical considerations for the phenomenon under study, reflecting the specific needs of the research.

4. Presentation and discussion of results

Frequency analyses conducted on the group composition revealed a trend among participants regarding the use of technologies and the level of experience within the innovation ecosystem of Curitiba. Among the 128 individuals in the sample, 86 (67.2%) indicated a higher use of BIM, while 42 (32.8%) reported a predominant use of GIS. This prevalence of BIM aligns with expectations for the case under study, given BIM's more immediate applicability in developing the urban built environment, such as buildings and infrastructure. Conversely, although GIS is relevant and has a more extended history, it tends to have a more limited application scope in this context. The nearly even distribution of experience with these technologies, where 67 respondents (52.3%) were considered novices (1 to 5 years of experience) and 61 (47.7%) were experienced (6 years or more), provided a favorable landscape for analyzing the impact of different experience levels on the dependent variable.

The mixed-effects model used in the study includes random terms for variables such as experience with BIM and GIS technologies (EXPGB), the intensity of use of these technologies (IUTGB), and significant fixed effects. With a sample of 128 individuals and a total of 9 estimated parameters, the sample size is at the lower bound of the general guidelines in the literature, which recommend between 10 and 20 observations per parameter ($90 \leq n \leq 180$) to ensure estimate precision (Hox, 1998; West; Welch; Galecki, 2022). Therefore, considering the model's complexity, the sample is adequate for the estimates of interest.

Thus, the sample benefited from a balanced distribution in terms of experience, and the observed disproportion in the use of technologies corresponded to expectations for the field of study on utilizing these technologies for generating urban management solutions. In this context, BIM is often the technology of choice for integration into constructive development strategies and technological alignment within organizations. Far from being considered a bias, this trend is an intrinsic characteristic of the area in focus. Therefore, it should be interpreted as such in analyzing model results and applying its conclusions to similar contexts. The prevalence of BIM thus reflects the reality of the technological ecosystem in question.

The mixed linear model analysis indicated a statistically significant relationship between KMTT and OCTAIE, evidenced by an F-value of 40.58, with a p-value of less than 0.001 (Table 1). Additionally, a VS-MPR of 928.67 was recorded. The statistical significance of the fixed effect KMTT suggests that the strategies and technological alignments integrating knowledge management and technical training play a significant role in adopting new technologies, such as BIM-GIS, aligning them with organizational objectives and processes within the innovation ecosystem of Curitiba. Investments in knowledge management, whether private or public policies, can result in significant improvements and adoption of new technologies within organizations in such an ecosystem. The importance of processes involving creating, managing, and disseminating knowledge within innovation ecosystems aligns with Chan and Chow's (2007) and El-Diraby's (2009) findings.

Table 1 - ANOVA Summary

Effect	df	F	p	VS-MPR
KMTT	11.76	40.58	< 0.001	928.67

Source: the authors. Note: The following variables were used as grouping factors for random effects: IUTGB and EXPGB.

The random effects analysis captured the heterogeneity associated with the intensity of the use of GIS and BIM technologies and the different levels of professional experience with these technologies. Specifically, the IUTGB random effects grouping factor encompassed the predominant use of BIM or GIS, while the EXPGB factor delineated the professionals' experience levels, categorizing them as novices or experienced. Incorporating random effects for these two groups provided a deeper understanding of how different levels of technological adoption and the intensity of use of each technology influence the organizational capacity to integrate new technologies into their processes and objectives. This understanding is relevant because, as Tidd and Bessant (2009) and David Schwartz (2006) pointed out, an organization's ability to adapt and absorb technological innovations is intrinsically linked to knowledge management and developing technical competencies.

Applying the Restricted Maximum Likelihood (REML) technique revealed a deviance of 413.35, which, although not interpretable in isolation, serves as a basis for calculating other relevant metrics. The log-likelihood reached a value of -206.67, indicative of the model's fit quality. This value, by itself, does not establish a measure of good fit but can be important for comparing different models; models with a higher (less negative) log-likelihood are preferable as they suggest a better fit to the observed data.

The model, with its 9 degrees of freedom, reflects the number of estimated parameters, and its parsimony is evaluated by the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), presenting values of 431.35 and 457.02, respectively. Lower values in these criteria are interpreted as indicative of a model with an adequate fit that does not exhibit excessive complexity. According to the literature, these indicators, while useful for model selection, should be considered alongside other fit measures and diagnostic evaluations for a robust and comprehensive analysis of the applied statistical model (Heck; Thomas, 2020).

The analysis of fixed effects estimates (Table 2) highlighted the significant impact of the KMTT variable on the dependent variable, strategies, and OCTAIE. The intercept, representing the overall mean organizational capacity to integrate and align emerging technologies when explanatory variables are at their reference values, was estimated at 3.70, with a standard error of 0.52. This intercept was statistically significant, with a p-value of 0.0023, indicating a robust effect with a t-value of 7.13 and a VS-MPR of 29.21.

Table 2 - Fixed effects estimates

Term	Estimate	SE	df	t	p	VS-MPR
Intercept	3.70	0.52	4.01	7.13	2.03×10^{-3}	29.21
KMTT	0.51	0.08	11.76	6.37	< 0.001	928.67

Source: the authors.

Similarly, the KMTT variable had a positive estimate of 0.51 with a standard error of 0.08, providing consistent evidence of its influence on the dependent variable. This was confirmed by a t-value of 6.37 and a high VS-MPR of 928.67, with a p-value significantly less than 0.001. The consistency of these findings with the model reinforces the relevance of knowledge management and technical training within organizations, underscoring that these variables are fundamental components for developing and integrating technological alignment strategies. The statistical significance of the intercept and the fixed effect variable within this model suggests that organizations have an intrinsic capacity for technological alignment, significantly enhanced by knowledge management and technical training.

The analysis of the correlation between the intercept and KMTT indicated that the intercept value of 1.00 confirmed it is perfectly correlated with itself, a mathematically inherent property of any variable. In contrast, the -1.00 correlation between the intercept and KMTT revealed a perfectly negative correlation. This suggests that within the random effects factor IUTGB (intensity of BIM or GIS use), an increase in the intercept effect is associated with a decrease in the KMTT effect, and vice versa. This finding implies that, within this specific group, knowledge management and technical training may have an inversely proportional impact on the organizations' base capacity for technological alignment.

Practically, the observed perfectly negative correlation may indicate a trade-off between the baseline effect, represented by the intercept, of organizational capacity to align emerging technologies and the effect exerted by knowledge management and technical training on this capacity. It was found that the incremental impact of knowledge management and technical training tends to be lower in organizations where the initial technological alignment is high. Conversely, knowledge management and technical training substantially impact organizations with a lower initial technological alignment. This dynamic suggests that organizations with a high initial level of technological alignment may not significantly benefit from increased knowledge management and technical training. In contrast, those with lower initial alignment may benefit more from strengthening these aspects. These interpretations show the importance of considering the existing level of technological alignment in organizations when evaluating the potential impact of knowledge management and technical training, for instance, through public policies or investments by private organizations in the innovation ecosystem.

The model analysis revealed that the standard deviation and variance attributed to the intercept of the EXPGB factor, representing the professionals' experience level (classified as novice or experienced), were both 0.00. This result indicates the absence of variation between the intercepts for different experience levels with BIM and GIS within this group. In other words, the analysis suggested that the average organizational capacity for technological alignment is not influenced by variability in professionals' experience among the groups considered in this factor. The homogeneity of the intercept and the KMTT variable implies that, as modeled, experience with BIM and GIS does not introduce significant differences in the organizations' capacity for technological alignment. Consequently, experience, as categorized and measured in this study, does not appear to contribute to variations in the dependent variable OCTAIE between different experience groups.

Retrospective model analysis revealed an extremely low standard deviation for the KMTT variable, corresponding to knowledge management and technical training, estimated at 4.35×10^{-6}, and an almost negligible variance of 1.90×10^{-11}. These results demonstrate that the fixed effect variable did not experience notable variations due to experience with BIM and GIS technologies. The detected uniformity may reflect homogeneity in the sample regarding the participants' experience or indicate that experience, as defined and operationalized in the study, did not produce a significant differential impact on the dependent variable. This finding suggests that, as measured by the research, professional experience was not a distinguishing factor for the organizational capacity to integrate and align emerging technologies such as GIS and BIM.

An emerging reflection from this result is that the distinction between professionals with less and more experience, established by the five-year threshold, may not be sufficiently discriminatory. This is likely because formal educational training in the field takes about four years at the undergraduate level, combined with five years of professional practice, tending to level the knowledge and skills of newer and more experienced individuals. This consideration points to the need to reassess experience distinction criteria in future research to capture nuances in adopting and integrating new technologies in the sector more effectively.

The residual variance estimates of the model revealed a residual standard deviation of 1.20 and a corresponding residual variance of 1.43, both of which are important for evaluating the model's fit. The residual standard deviation of 1.20 reflects the average degree of dispersion of the residuals concerning the model's predictions; this means that, in practice, most dependent variable observations deviate by approximately 1.20 units from the model's predictions. The residual variance of 1.43 provides a measure of dispersion detailing the variation in the residuals, indicating the degree of variation not explained by the model.

The relevance of these estimates to the model's adequacy is contextual. Generally, a relatively low residual standard deviation and corresponding residual variance suggest that the model adequately captures the variability in the data, considering the scale of zero to ten used. This indication is crucial to confirm the model's robustness and precision in explaining the dependent variable, especially in complex studies in information technologies and urban studies.

The random effects estimate for the IUTGB factor revealed how the predominant use of BIM or GIS affects the strategic organizational capacity for technological alignment and the influence of KMTT, as shown in Table 3. The random intercept for organizations predominantly using BIM was estimated at 0.04, indicating a slight variation above the overall mean capacity for technological alignment. For organizations with predominant GIS use, the intercept was -0.04, suggesting a slight variation below the overall mean. These variations, although subtle, reflect differences in technological alignment capacity attributable to the predominant use of one technology over the other.

Table 3 - Random effects estimates on the intensity of GIS and BIM technology use

IUTGB	(Intercept)	KMTT
BIM	0.04	-4.44×10^{-3}
GIS	-0.04	4.44×10^{-3}

Source: the authors.

Furthermore, the slope associated with KMTT was -0.04 for the BIM group, signaling a minimal negative impact on knowledge management and technical training. The GIS group's slope was 0.04, indicating an equally small positive effect. The opposition and symmetry of the slopes for BIM and GIS may reflect a significant interaction between the type of technology used and the effectiveness of knowledge management and technical training. This interaction warrants further investigation into how different technologies influence an organization's capacity to align its technological strategies.

However, it is essential to note that the magnitude of the random effects was relatively small for this investigation, on the order of 10^{-3}, which may be considered insignificant in many practical contexts. Nevertheless, the symmetry of these opposing effects, with a magnitude of 4.44×10^{-3}, might indicate that knowledge management and technical training strategies must be tailored according to the predominant technology in the organization to optimize technological alignment.

The results seen in Table 4 for both experience levels (EXPGB) indicated no variation in the intercept between individuals with different experience levels with BIM or GIS technologies. The estimates for the "Beginners" and "Experienced" groups were 0.00. This indicates that experience alone did not contribute to significant variation in technological alignment capacity after controlling for fixed effect variables. From the perspective of random effects, this finding suggests that experience is not associated with differences in the mean technological alignment capacity once controlled for other variables present in the model.

Table 4 - Random effects estimates for experience with GIS and BIM

EXPGB	(Intercept)	KMTT
Beginners (1 ~ 5 years)	0.00	-4.17×10^{-10}
Experts (6+ years)	0.00	4.17×10^{-10}

Source: the authors.

The absence of variation in the intercepts signals that considering the model's fixed effects, experience with BIM or GIS does not explain the variation in technological alignment capacity between groups with different experience levels. In other words, experience, as measured and categorized in the study, did not demonstrate itself to be a significant differentiating factor in the capacity of organizations to integrate and align emerging technologies such as GIS and BIM. This finding reinforces the need to consider broader factors beyond experience to explain the organizational capacity for technological alignment in innovative and technologically advanced contexts.

For the "Beginners" group, the slope associated with knowledge management and technical training (KMTT) was -4.17×10^{-10}, indicating this variable's small, almost negligible, effect on technological alignment capacity. For the "Experienced" group, the slope was positive at 4.17×10^{-10}, which, although numerically identical in magnitude, was opposite in direction to the value found for the "Novices" group. This implies that, regarding random effects, knowledge management and technical training have a small but positive impact on the technological alignment capacity of experienced users.

The symmetry of these coefficients may suggest a balance in the modeled effects that, in practice, do not result in observable or significant differences in technological alignment capacity resulting from knowledge management and technical training. In other words, the analysis suggests that, regardless of the level of user experience, the influence of knowledge management and technical training on technological alignment capacity is minimal. These findings highlight the complexity and the need to consider multiple factors beyond individual experience and knowledge management to fully understand the capacity of organizations to integrate and align emerging technologies into their processes.

The estimated marginal means for the KMTT variable revealed, as it can be seen in Table 5, significant differences relative to the null hypothesis across the three analyzed lines. For the first line, with a KMTT value of 4.85, the estimated marginal mean was 6.19, with a standard error of 0.16. The 95% confidence interval ranged from 5.87 to 6.50, and a very high z-test value of 38.37, accompanied by an extremely low p-value ($p < 0.001$), indicated a significant difference compared to the null hypothesis.

Table 5 - Estimated marginal means

Line	KMTT	Estimate	SE	Lower	Upper	z	p†	VS-MPR
				95% CI				
1	4.85	6.19	0.16	5.87	6.50	38.37	< 0.001	∞
2	6.19	6.87	0.11	6.65	7.10	60.29	< 0.001	∞
3	7.52	7.56	0.15	7.26	7.86	49.69	< 0.001	∞

Source: the authors. Note: † p-values correspond to the null hypothesis test against 0.

The marginal means for the other two lines were 6.19 and 7.52, with standard errors of 0.11 and 0.15, respectively. The confidence intervals for both lines did not cross zero, and the z-test values were 60.29 and 49.69, both significant with p-values less than 0.001. A VS-MPR considered infinite for all estimates suggests a strength of evidence against the null hypothesis so compelling that the statistical model regards it as virtually irrefutable.

These results indicate a strong and significant association between the KMTT and dependent variables. This consistent evidence reinforces the importance of knowledge management and technical training within organizations, highlighting their central role in technological alignment capacity, as seen by the statistical model employed in the research.

The mixed linear model results analysis revealed a statistically significant association between KMTT and the dependent variable, representing the organizational capacity for technological alignment. The first line of the Table 6 shows an estimated marginal mean of 4.85 for KMTT, with a standard error of 0.16 and a 95% confidence interval ranging from 5.87 to 6.50. The z-test resulted in a value of 38.37, and the p-value was less than 0.001, indicating statistical solid significance and robust rejection of the null hypothesis. The importance is reinforced by the VS-MPR, which is considered infinite and provides compelling evidence against the null hypothesis.

Table 6 - Estimated trends

KMTT	KMTT (Slope)	SE	Lower	Upper	z	p†	VS-MPR
			95% CI				
4.85	0.51	0.08	0.36	0.67	6.37	< 0.001	$8.69\times10^{+7}$
6.19	0.51	0.08	0.36	0.67	6.37	< 0.001	$8.69\times10^{+7}$
7.52	0.51	0.08	0.36	0.67	6.37	< 0.001	$8.69\times10^{+7}$

Source: the authors. Note: † p-values correspond to the null hypothesis test against 0.

The second line shows an estimated marginal mean for KMTT of 6.19, with a standard error of 0.11 and a 95% confidence interval ranging from 6.65 to 7.10. The z-value recorded was 60.29, with a p-value significantly less than 0.001, maintaining the trend of significance. The third line follows with an estimated marginal mean of 7.52, with a corresponding estimate of 7.56, a standard error of 0.15, and a 95% confidence interval between 7.26 and 7.86. With a z-value of 49.69 and a p-value below 0.001, the data suggest a strong and consistent association between knowledge management and technical training and the organization's technological alignment capacity.

The results from the mixed linear model, as presented in the Table 6, consistently demonstrate across the three examined lines that an increase in knowledge management and technical training is associated with an increase in the dependent variable, showcasing the organizational capacity for technological alignment. The KMTT slope variable maintained an estimated 0.51 with a standard error of 0.08, indicating a uniformly positive and significant relationship with the dependent variable at all examined independent variable levels. These findings emphasize the critical importance of knowledge management and technical training within organizations, highlighting that investments in these areas are central to fostering consistent technological alignment strategies.

These trends' consistency and statistical significance corroborate the existing literature, specifically the theories of Chan and Chow (2007) and El-Diraby (2009), which emphasize the vital importance of knowledge management and technical training capacities for developing and implementing innovative technologies within innovation ecosystems. The constancy of the KMTT effect across different estimated marginal means reinforces the understanding that technical training and knowledge management are fundamental and transversal factors for strategic technological alignment in organizations operating in complex urban management contexts.

5. Conclusion

The in-depth investigation of the interaction between knowledge management, technical training, and organizational capacity for technological alignment in urban development environments elucidated the direct impact of these competencies on the effectiveness of technological alignment strategies. Additionally, the study examined how experience with specific technologies such as BIM and GIS and the intensity of their use influence these effects. The mixed linear model captured intra-group and inter-group variability, reflecting the complexity of organizational structures and the dynamics of technological capacities. The results align with the objective of this article, deepening the understanding of how knowledge management and technical training interact with technological alignment and highlighting the importance of these elements for the progress of technological integration strategies in intricate urban contexts. This research underscores the significance of continuous skill development and knowledge management in organizations. It highlights the need to consider contextual variables—such as experience and technology use—to optimize technological alignment and foster organizational innovation in technological ecosystems that support urban management.

The results corroborated the hypothesis that knowledge management and technical training enhance organizational capacity for technological alignment. A positive correlation was found between increments in knowledge management and technical training (KMTT) and advances in technological alignment capacity (y). These findings indicate that investments in these dimensions result in tangible benefits in integrating new technologies. Additionally, the study elucidated that experience and the intensity of BIM and GIS technologies (EXPGB and IUTGB, respectively) significantly impact both the starting point and the evolution of technological alignment capacity. In Curitiba, a city recognized for its predisposition towards technological innovation, it was observed that different levels of experience and use of these technologies lead to distinct trajectories in developing technological capacities. These results support the investigated hypothesis while emphasizing the complexity of Curitiba's technological ecosystem, highlighting the strategic importance of knowledge management and technical training for the effectiveness of organizational operations amid technological innovation.

Although the research centered on Curitiba's context offers fundamental contributions to a technologically advanced urban ecosystem, it is necessary to consider the complexity and diversity of scenarios in which knowledge management and technical training manifest. This broader approach is crucial for promoting effective solutions in GIS and BIM, thus driving the adoption of CIM in various urban contexts. Therefore, generalizing the findings to other realities may be restricted, given the uniqueness of Curitiba's cultural, economic, and technological variables. Despite its robustness, the methodology based on Mixed Linear Models is recognized to have limitations in addressing more intricate dynamics and non-linear interactions among the studied variables. For subsequent research, it would be promising to expand the analysis to encompass multiple innovation ecosystems, allowing for intercultural and interregional comparisons that could elucidate distinct patterns of technological alignment. The application of advanced analytical methods, such as structural equation modeling or network analyses, could reveal more subtle aspects of the relationships between knowledge management, technical training, and technological alignment. Moreover, longitudinal studies could provide a more dynamic perspective, tracking the transformations of technological integration strategies and how they respond to internal and external organizational changes.

Declaration

The authors declare the use of generative artificial intelligence, specifically ChatGPT 4.0, in text review for the purpose of identifying spelling errors. After using this tool/service, the authors have reviewed and edited the content as necessary and assume full responsibility for the content of the publication.

Acknowledgements

This research was supported by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior - Brasil (CAPES) - Financing Code 001.

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