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Location Analytics and Decision Support: Reflections on Recent Avancementa, a Research Framework and the Path Ahead

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1. Introduction

The expansion in analytics and big data over the past decade has included a rapid growth in locational analytics, spatial analysis, and geographic information systems and science. Although research in Decision Support Systems (DSS) has typically tackled spatial decision problems through connections to geographic information systems (GISs), recent research has focused on the benefits from combining the two bodies of knowledge and research streams in addressing important challenges in delivering quality decisions in settings with location-al/spatial components. Consequently, research in spatial decision support now seeks to take advantage of the advances in analytics, big data and cloud based decision support. This work incorporates spatio-temporal big data, mobile location-based services, 3-D, location in the sharing economy, space-time, and location-based social media.

The goal of this special issue is to present explorations and knowledge enhancement on the cutting edges of decision making involving location and place. The work presented includes new problem areas, data sources, methodologies, and applications in today's more complex and data-rich decision-making environments. To provide a context for the ideas and findings in the special issue articles, this editorial reviews and extracts broad themes and categorizations from a selection of over two dozen past articles published in DSS that combine location analytics (LA), non-location analytics (NLA), and decision support (DS). We then propose a generic framework for LA/NLA/DS research, briefly summarize the eight articles in the special issue, and then outline the directions the field of location analytics and decision support is moving towards. Finally we discuss what gaps in the LA/NLA/DS research landscape need to be addressed by future research.

2. Location analytics and decision support: synopsis of extant research

Location analytics (LA) refers to the contemporary concept of using specialized spatial analysis techniques to understand spatial arrangements, patterns, groupings and relationships in geographically referenced phenomena. Methods include overlays, buffers, hot spot analysis, spatial cluster analysis, spatial autocorrelation, proximity polygons, spatial econometrics and other techniques. Non-location analytics (NLA) refers to analytics methods that do not include spatial dimensions, such as non-spatial statistics, forecasting, optimization, sensitivity analysis, multi-criteria evaluation, simulation, and data mining. The research reviewed in this section has both location analytics and non-location analytics, which, together, provide decision support (DS). The term spatial Decision Support Systems (SDSS) refers to a decision support system that includes spatial components.

In examining past research in LA/NLA/DS, this journal provides a rich corpus of investigation, which is the focus of the literature examined here. We chose this path not only due to limited space for the editorial, but also because of this journal's leadership in publishing in this area. For instance, in a study [10] of spatial papers published in leading IS journals during 1988–2012, *Decision Support Systems* was identified as the leader with 54% of published articles, followed by *Communications of the ACM* with 17%.

The papers in Table 1 appeared between 2002 and 2017 in *Decision Support Systems*, and were selected for discussion based on having substantial location analytics and decision support content. The body of research can be understood by considering: (a) the problem being addressed and research questions, (b) methodologies, (c) location analytics content, (d) non-location analytics and decision support content, (e) types of relationships between location analytics and decision support, and (f) empirical analysis and validation. Since there is not enough space to examine each of the over two dozen papers on these six components, the prior LA/NLA/DS landscape is discussed with examples to illustrate pertinent points.

2.1. The problem areas and research questions

Roughly half of the studies concern solving problems in transportation/routing, location siting, and urban issues (see Table 1). Other problems include: 1) gaining understanding of the cognitive aspects of LA/NLA/DS, 2) conceiving conceptual theory and frameworks for LA/NLA/DS, 3) designing a geospatial information utility for LA/NLA/DS, 4) designing spatial decision support for disruption of links in critical national infrastructure, 5) developing structural theory and testing of locational privacy issues with application to marketing decisions, 6) predicting small business failures using social media locational data, and 7) developing an integrated predictive model of human mobility and movement intention based on a person's GPS trajectories [7,8,25,32,35,41]. The research questions underpinning these studies mostly concern how to construct LA/NLA/DS models, what are the implications of the results of empirical applications, and what is learned from experimental outcomes.

2.2. Methodologies

A variety of methodologies have been utilized in past research. In the papers that focus on constructing SDSS, methods include optimization

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Table 1
Characteristics of 25 prior articles in Decision Support Systems on location analytics and decision support.

Article ++++++++	Spatial level[c]	Purpose of the study and methodology(ies)	Modeling type	Empirical testing
A decision support system for predictive police patrolling [5]	2	Algorithm development, patrol sector optimization.	predictive	yes
A GIS-based multicriteria spatial Decision Support Systems for planning urban infrastructures [7]	2	Building an SDSS for city planning. Design science, not formal.	prescriptive	yes
Spatial decision support systems: an overview of technology and a test of efficacy [8]	2	Lab experiment to test differences in task solutions for SDSS users versus those using printed materials.	descriptive[a]	yes
Spatially enabled customer segmentation using a data classification method with uncertain predicates [9]	4	Spatial data classification techniques utilizing spatial predicates to accomplish customer segmentation	descriptive	yes
A DSS for bicriteria location problems [11]	2	Site selection. Build a DSS for bi-criteria location problem. Design science, not formal.	prescriptive	yes
Key challenges and meta-choices in designing and applying multi-criteria spatial Decision Support Systems [12]	2	Theorizing. Development of a framework to understand integration of SA and multi-criteria evaluation methods.	descriptive[b]	no
Predicting crime using Twitter and kernel density estimation [14]	4	Twitter-specific Dirichlet allocation modeling and historic crime density to predict density patterns by crime type.	predictive	yes
A GIS support Ant algorithm for the linear feature covering problem with distance constraints [17]	2	Bi-objective optimization modeling with LFCP-Ant algorithm. Design science, not formal.	prescriptive	yes
Exploring the influence of perceptual factors in the success of web-based spatial DSS [19]	2	Development and test of a conceptual model for web-based SDSS	descriptive	yes
Spatial decision support for assisted housing mobility counseling [20]	2	Design of web-enabled SDSS for housing search and placement of low-income families. Design science, not formal.	predictive	yes
A GIS-based decision-support system for hotel room rate estimation and temporal price prediction: the hotel brokers' context [21]	2	Development of an SDSS containing a hedonic pricing model and dynamic model. Design science, not formal.	prescriptive	yes
A decision-support tool for a capacitated location-routing problem [24]	2	Design solutions to capacitated location-routing problem, with sequential heuristic. Design science, not formal.	prescriptive	no
Geospatial information utility: an estimation of the relevance of geospatial information to users [25]	4	Design a geospatial information utility that computers a score of spatial and content accuracy.	descriptive	no
A link-focused methodology for evaluating accessibility to emergency services [26]	2	Use network-science/graph theory closeness concept to measure critical accessibility to emergency services from a road network.	descriptive	yes
A web-based spatial decision support system to optimize routes for oversize/overweight vehicles in Delaware [30]	4	Design of a permit routing SDSS for Delaware, using network optimization methods. Design science, not formal.	prescriptive	yes
A web spatial support system for vehicle routing using Google Maps [31]	4	Support for multiple-vehicle routing problems. Design science, not formal.	prescriptive	yes
Going the last mile: a spatial decision support system for wireless broadband communications [32]	4	Development of an SDSS for wireless network planning of equipment locations. Optimization for high profit and low cost. Design science, not formal.	prescriptive	yes
Decision support for network disruption mitigation [33]	2	Identify the weak links in critical network infrastructure and support survivability, using optimization, statistics, and what-if analysis. Design science, not formal.	predictive	yes
On the brink: predicting business failure with mobile location-based check-ins [35]	3	Logit Model to predict business failure, based on customer check-ins including those from nearby competitors from Foursquare.	predictive	yes
The seaport service rate prediction system: using drayage truck trajectory to predict seaport service rates [36]	4	Building a drayage service rate prediction system, using geo-fencing and for optimization of service time.	predictive	yes
Metadata as a knowledge management tool: supporting intelligent agent and end user access to spatial data [38]	4	A metadata architecture including a data model, database features, metadata, and relationship to knowledge management and GIS.	descriptive	no
The personalization privacy paradox: an exploratory study of decision making process for location-aware marketing [39]	3	Development of a locational privacy calculus model based on structural equation modeling.	descriptive	yes
Spatial analysis with preference specification of latest decision makers for criminal event prediction [40]	3	Application of discrete choice theory and data mining for point process spatial models.	predictive	yes
Human mobility discovering and movement intention detection with GPS trajectories [41]	4	Data mining of historical trajectories to predict interesting locations and frequent travel sequences, based on a trajectory partitioning algorithm.	predictive	no
Using 3D interfaces to facilitate the spatial knowledge retrieval: a geo-referenced knowledge repository systems [42]	2	Examination of how 3-D interfaces facilitate the use of the map information. Prototype system development and conduct lab experiments to compare 3-D with 2-D mapping.	descriptive	yes

[a] Descriptive – experimental.
[b] Descriptive – conceptual.
[c] Represents complexity levels of spatial analysis and modeling, described in Section 2.3.

techniques such as bi-objective optimization [17], network optimization [30], and capacitated location routing with sequential heuristics [24]. Several studies utilized statistical models including a logit model to predict business failure [39], structural equation modeling to estimate locational privacy [35], and a hedonic pricing model [21], while experimental designs were used to assess cognitive and behavioral aspects of LA and DS [8].

On the spatial side, some studies used descriptive spatial analysis of point locations and polygons, while several studies used more sophisticated GIS methods including 3-D display [42], geographical flow diagrams with flowlines [33], and multi-layer urban mapping [11].

2.3. Location analytics content

A literature review study of leading MIS journals showed that the location analytics side of this special issue's research focus has trailed the more heavily researched non-location analytics side [10]. Examination of prior spatial research needs to delve further and identify the levels of location analytics previously incorporated. For this we refer to a well-known book that introduced a classification for the strength and depth of location analytics [27]. The classification starts with simple map display of raw values for geospatial phenomena and scales up in complexity to complicated models that incorporate spatial modeling of such phenomena. The classification has the following four levels.

1. *Spatial data manipulation*. This is an elementary use of locational analysis that simply produces the raw geographic information; sometimes referred to as "dots on a map," because the dots as raw data are not further organized or elaborated on to become information or knowledge [27]. Spatial data manipulation does not have a location analytics component.
2. *Spatial data analysis*. This is more descriptive than Level 1, and often exploratory. Techniques of spatial analysis are used [22,23,27] including overlays, buffering, spatial autocorrelation, hotspot analysis, proximity polygons, 3-D, rastering, location quotients, Huff modeling, and spatial econometrics. Spatial data analysis considers the geospatial and geometric relationships of the mapping elements. For instance, layering includes analyzing the relationship of one mapping layer (e.g., a layer of locations of distribution centers) with another mapping layer (e.g., a layer of zip code polygons).
3. *Spatial statistical analysis*. At this level, data are used in estimating a statistical model or solvable optimization model that recognizes spatial properties [2,6].
4. *Spatial modeling*. This level uses heuristics, simulations, and combined methods in an integrated model that are expressed spatially. The goal is to answer questions such as can the model express geographic flows of persons and material objects, optimize the location of business offices and facilities, or simulate real world complex locational environments and situations [26]. Spatial modeling goes beyond the solvable spatial statistical models in step 3 and consists of deterministic or stochastic modeling and simulation that includes spatial elements.

A simple analogy to Google Maps would be that level 1 is the Google map display of raw features, level 2 would compute squared distances between selected features on the map, level 3 would determine statistically significant hotspots of the highest real estate prices for a region, and level 4 would program a simulation, using Google's Keyhole Markup Language (KLM) and based on the spatial patterns and volumes of historical traffic flows that would simulate the region's traffic flows on its major highways on an hourly basis over the next 24 h.

Referring to the articles in Table 1, thirteen are at Level 2, three at Level 3 and nine at Level 4. At Level 4, Santos et al. [31] developed and integrated LA/DS model of vehicle routing solutions for Coimbra, Portugal. Ray [30] illustrated spatial modeling at Level 4 by programming an integrated solution to optimal truck routing in Delaware, as did Scheibe et al. [32] in estimating view sheds for cell towers based an integrated model using complex criteria. Crossland et al. [8] operated at Level 3, utilizing the summing of weighted layers and mapping of a statistical index, as does Huang et al. [17] in utilizing geographical cluster analysis.

Meeks and Dasgupta [25], at Level 2, performed behavioral experiments using SDSS models of varying complexity, incorporating spatial analysis including overlays and urban product market areas. Further examples are [12], which emphasized the benefits of overlays of planning criteria maps, while [20] utilized multiple types of spatial features at this level. Also at this level, [33] offered the capability to disaggregate a national network disaster map into nodal impacts showing flow lines with thicknesses, while [17] converted continuous inputs of places into a raster map with discrete cells and grid coordinate systems.

2.4. Non-location analytics and decision support content

A majority of previous work on location analytics and decision support also incorporated non-location related components such as the underlying (non-locational) research problems, data utilized and/or generated, and non-locational analytics methodology. As examples of non-locational components in this collection of articles, [35] tackled the popular bankruptcy prediction problem using location-tagged social media along with more typical business characteristics previously used in failure prediction, while [21] predicted hotel room rates using both facility and location data. In other examples, Gerber [14] used Twitter data, which has both location and non-location content in crime prediction, and [36] predicted service rate of a seaport using mostly geo-spatial data. The non-location data used in this body of work consisted of customer demographics and store characteristics [9], hotel facilities, room amenities, and hotel categories [20], prices and restaurant ratings [35], and textual content of tweets [14].

Another subset of the reviewed research used non-location data and non-locational analytics techniques in addressing location problems. For example, [32] used client income, service fees, and equipment costs in a binary optimization model to determine optimal placement of wireless towers in a rural county in mid –Atlantic USA. Customer demand, vehicle capacity [24,31], vehicle size and weight [30], and facility (depot) capacity [24] along with location data have been used in vehicle route optimization problems. Johnson [20] introduced a system that used landlord, building and individual unit data along with multi criteria decision making (ranking) techniques for support in neighborhood selection by clients in the Section 8 Housing Choice Voucher Program.

This examination of prior research indicates a variety of ways that locational and non-locational elements can be combined to address important research questions. The next subsection proposes a way the relationship between these elements can be categorized.

2.5. Types of relationships between location analytics, non-location analytics and decision support

The integration of location analytics with non-locational components can range from separate modules with loose connectors to fully data-integrated systems and/or software. Since integration is hard to quantify, this section discusses three dimensions in which LA and NLA may be integrated and the criteria to determine whether integration is strong or weak.

The dimensions of integration we propose are: (a) conceptual integration, (b) algorithmic/software integration, and (c) integration as it appears to the user. *Conceptual integration* occurs when the design of an SDSS does not uncouple and separate the GIS/spatial module from that of the non-spatial analytics and decision support. A study at this level might be one that conceptualized the integration of GIS with marketing information systems. *Algorithmic/software integration* refers to algorithms that unite the LA and NLA computations in the software. An example of algorithmic integration would be a predictive model was developed to predict crime through an algorithm that includes neighborhood places and Twitter-specific topics. *Integration based on Appearance to Users* occurs if the user is provided a unified, integrated interface of the LA, NLA, and DS interactivity and displays. In some studies, even though LA is conceptualized as a separate part of a broader model and kept apart in the software, to the user the model appears integrated. An example would be a model of spatial decision support for disruption of critical network nodes comprised six separate analytical parts conceptually and algorithmically, but the user was seamlessly able to view an integrated dashboard showing mapping, graphics, and tables in the same display, without being aware of the conceptual and algorithmic separation of LA, NSA, and decision support.

Several examples demonstrate the complexity of approaches to LA/NLA/DS integration. Strong LA/NLA/DS integration is exemplified by a study of vehicle route optimization in Coimbra, Portugal [31]. The authors were confronted with a challenging city for route optimization, Coimbra having an old city center with "very narrow and one-way streets, high traffic, and endemic congestion problems" [31]. The need to prescribe better routing encouraged the conceptual integration of a geographic route network and optimization, along with need for strong and efficient LA/DS integrated software architecture and data flows, which is seen by the inclusion of Google mapping at three key points in the data flow ([31], Fig. 1). A high level of user integration is evident in a mini-dashboard. In another example of strong integration [21], GIS available from the Java OpenStreetMap Editor was integrated with code modules using R software, SQL, Weka data mining, MDS (multidimensional scaling app) and graphing. The user interface was almost seamless between spatial and numeric results, and conceptual integration was emphasized.

Weak LA/NLA/DS integration was demonstrated in a study of predicting business failure for restaurants in New York City [35], based on data from location-based service providers Foursquare and Yelp. Although imaginative, the nearest neighbor algorithms/software were separated from the neural network and logit tools for non-spatial analysis. Conceptual integration of LA/NLA is weak since the neural network concepts are not linked with those of nearest neighbor. Lastly, no user interface integration was given, and the model was in the user testing stage.

2.6. Empirical testing of algorithms, systems, or approaches

Empirical testing is important in validating the often complex modeling of SDSS, as empirical testing considers the real-world capabilities, benefits, and limitations of the model. 80% of the articles examined report empirical testing. An example of the benefits of empirical validation is the aforementioned spatial displays of traffic patterns in the city of Coimbra, Portugal [31]. The application provided detailed vehicular networks for the city, vibrantly illustrated with a Google Map add-on. For a particular route, all the links can be illustrated so the tradeoffs of duration service and route length are visually available and assumptions can be flexibly changed. The full capabilities of this creative routing

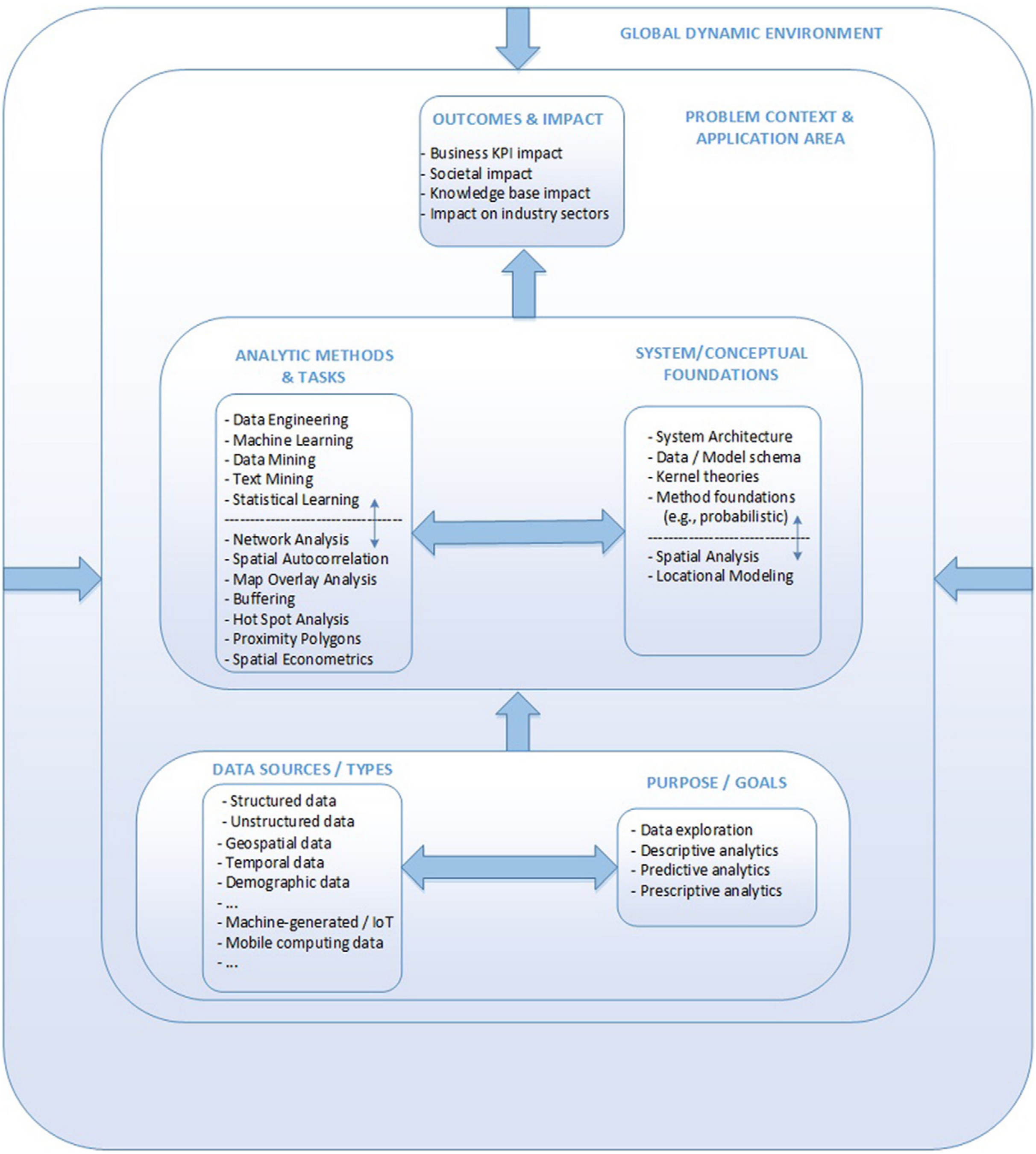

Fig. 1. A framework of location analytics and decision support research.

system would have lacked validation without the empirical testing. One desirable capability for articles published in journals such as *Decision Support Systems* would be to encourage posting of live demos, so that a reader could run their own hands-on empirical tests.

The next section proposes a broad framework that seeks to integrate the major concepts in the field of location analytics and decision support.

3. A research framework for locational analytics and decision support

Fig. 1 shows an overall framework depicting key elements in a typical locational analytics and decision support research project. This framework also provides an abstraction based on the observations from the extant body of work in this area, as discussed in Section 2. The goal of the framework is to provide a generic way of linking new research in this area to prior or existing work including the articles in this special issue.

The framework emphasizes the influence of the changing global environment on research. The relevance and prominence of the research issues can be conceived as a function of the broader dynamic environmental settings. For instance, the mobile technology revolution over the past decade has led to proliferation of location-based data. Privacy issues [29,39] that were at the forefront until only a couple of years back are giving way to newer perspectives on analyzing consumer behavior in which consumers are seen to seek convenience and spontaneity over privacy concerns [15]. The emergence of the sharing economy is another such environmental change [34]. Situated in the context of such environmental issues at large is the more specific problem area that research aims to investigate. Studies typically hone in on a more focused problem context for addressing decision support issues in general and locational analytics issues in particular.

Next, as researchers and practitioners analyze a problem context in their application domain of interest, potential issues of relevance often emerge as candidate study topics. These issues of interest are then formalized as research objectives or goals articulating the purpose of the study. Given the emergence and availability of new data sources (e.g., Internet of Things, social media, volunteered geographic information, drones, and LIDAR), the stage of articulating the purpose or goal of a study is intricately linked with the availability of data from accessible data sources. In several instances, rich data sources serve as stimulants for formulating interesting research questions in the application domain. Fig. 1 illustrates this notion with the link shown between the data sources and study purpose/goals. Further, we note that the purpose of the study can be mapped onto one or more variants of analytics, namely data exploration, descriptive, predictive, and prescriptive. For instance, exploratory data analysis, often with goal of pattern or trend discovery, is employed in theory formulation through use of descriptive analytics.

Depending on the research purpose, relevant analytic methods and techniques, in tandem with appropriate system/conceptual foundations, are brought to bear on addressing the problem. As discussed in Section 2, scholars employ one or more locational and non-locational analytic methods and techniques to tackle pertinent decision support research objectives. In Fig. 1, the opportunity of integration of LA and NLA methods is indicated by the partition line and two-way arrows connecting LA and NLA analytic methods and tasks. Notably, the development of new analytic methods or application of existing methods is closely tied to the type of data (e.g., text, temporal, geospatial, etc.) as well as the research goal, i.e., descriptive, predictive or prescriptive. Further, the nature of the data in terms of whether researchers are dealing with "big data" [37], as generally characterized by volume, variety, and velocity, or not, is also a key determinant of the applicability of extant analytic techniques.

Last, but not least, in the development or application of analytic techniques, system/conceptual foundations also play a key role. System/conceptual foundations may vary in form in different studies. For example, a spatial DSS based on a system architecture that integrates various modules to address prescriptive analytics goals is proposed in [31]. Here the system architecture serves as the foundation based on which the data and model (analytic method) components are integrated in a systematic manner. Under system/conceptual foundations, locational conceptual theory can be integrated to a greater or lesser extent with non-locational conceptual theory, which is shown by partition line and two-way arrow connecting LA and NLA concepts.

The extent to which the research goals are successfully addressed is gauged in the evaluation stage through analyses of outcomes including testing of the research model and its implications. The very nature of analytic methods-based research in locational analytics and decision support often maps closely to the design science research paradigm [16,28]. As such, the various evaluation methods in design science research are pertinent in evaluating the organization or business impact, societal impact, and more broadly impact or contribution to the knowledge-base of the field.

The framework shown in Fig. 1 can also be used for linking and synopsizing how the manuscripts in this special issue, summarized in Section 4, contribute to the advancement of the area of locational analytics and decision support, and to identify what research gaps still remain.

4. Summary of contributions to special issue

We are indebted to the efforts of a geographically dispersed array of talented researchers and authors for their significant contributions to this Special Issue. In this section, we briefly discuss their contributions and summarize them.

The paper by Deodhar et al., "Geography of Online Network Ties: A Predictive Modeling Approach" is notable since the authors examine an important problem: do electronic intermediaries alleviate the geography bias between individuals/entities that are part of a globally dispersed peer network or do they prefer to form ties with proximal peers? First, the authors employ machine learning to cluster pairs of nations based on distance measures and network ties for a unique dataset comprised of traders with known national affiliations in an online social trading platform. This is followed by predictive analytics to assess the extent to which geographic distances predict strength of network ties. The finding that geographic distance, compared to psychic distance, is the strongest predictor of network ties underscores the importance of geographic barriers in contrast to differences in language, religion, education, economic development, and political landscape between countries. This has decision support implications in online networking contexts.

The contribution of authors Lozano, Schreiber, and Brynielsson, "Tracking Geographical Locations using a Geo-Aware Topic Model for Analyzing Social Media Data," focuses on tracking how discussion topics evolve in social media spatiotemporally. The authors have designed and evaluated a model, known as the streaming latent Dirichlet allocation (SLDA) topic model, for tracking online discussions on topics, and the corresponding persons, organizations, and locations, over time. Using two different Tweet corpora related to the 2016 U.S. Presidential elections, the SLDA topic model was implemented, used for automatic discovery and geographical tracking of election topics, and found to be an effective model for tracking geographical trends and topical locations during the elections. As topic modeling rapidly emerges as an effective way to arrange large bodies of unstructured text into representative topics, tracking the geographic locations where important topics are discussed over time enhances knowledge of interested stakeholders. Furthermore, it can assist in effective allocation of scarce resources, for example to tackle the fallout from a customer service misstep in the service sector or manage a crisis caused by harmful leaks from a rival campaign during an election cycle.

"Facility Location Using GIS Enriched Demographic and Lifestyle Data for a Traveling Entertainment Troupe in Bavaria, Germany," by North and Miller, has enriched a variant of the classic maximal coverage location problem (MCLP) common in the Operations Research literature with demographic and consumer spending data to determine optimal locations for a traveling entertainment troupe in Germany. Employing the combination of mathematical optimization with geographic parameters and attributes such as coverage distance, travel time, and consumer lifestyle tapestry, the authors identify optimal locations of shows that maximize demand coverage within specified distance thresholds while maintaining dispersion of selected locations to prevent cannibalization of demand. Greater availability of precise travel distance and travel time estimates in actual transportation networks, along with lifestyle choice and consumer spending data, provides increased opportunities to integrate location analytics and optimization modeling to solve complex demand coverage problems in many resource-constrained settings. This paper provides a thorough illustration of the power of prescriptive analytics to solve such a real-life facility location problem.

The paper "A bi-objective two-stage robust location model for waste-to-energy facilities under uncertainty" by Hu, Liu, and Lu is another illustration of the development of a prescriptive analytics-oriented decision support approach, this time to model a complex obnoxious facility location problem. Location of waste-to-energy (WTE) facilities is sensitive due to environmental and economic implications of location decisions and consequent implications for urban sustainability. The authors situate the problem of optimally locating WTE incinerators in the city of Shanghai, China, one of the world's largest urban agglomerations. A bi-objective two-stage optimization model that minimizes annual government spending on one hand and environmental disutility on the other is enriched by geographically-referenced inputs such as locations and sizes of population centers, potential WTE locations, transportation costs between population centers and WTE locations, as well as between population centers and sanitary landfills. WTE facilities are increasingly important for strategic sustainable development; Hu et al.'s Special Issue contribution demonstrates the potential of location-based prescriptive analytics to optimize locations of such facilities.

In "Designing Utilization-based Spatial Healthcare Accessibility Decision Support Systems: The Case of a Regional Health Plan," Li, Vo, and Randhawa propose a novel utilization-based framework to integrate non-spatial factors such as age, gender, race/ethnicity, and language within spatial healthcare accessibility research. Such demographic and socioeconomic attributes have the potential to add rich nuance to healthcare accessibility models and yet are traditionally ignored. The framework developed by the authors uses predictive analytics to derive categorical and factor weights for healthcare needs of specific population subgroups based on non-spatial attributes. A Spatial Decision Support System (SDSS) that blends weighted non-spatial attributes with spatial measures of supply (healthcare provider locations), demand (population centroids), distances, and drive times, helps to identify physician shortage areas. Additionally, descriptive maps depicting utilization enables decision makers to adjust healthcare utilization for different age groups, gender, race/ethnicities, and languages spoken among a healthcare provider's catchment areas. This can be critical to maintain adequate service levels especially in rural areas as well as to efficiently allocate scarce resources in real-life healthcare settings.

The paper "Preventing Traffic Accidents with In-Vehicle Decision Support Systems - The Impact of Accident Hotspot Warnings on Driver Behavior" by Ryder et al. seeks to examine in-car driver behavior in light of a decision support system (DSS) within a vehicle that issues accident hotspot warnings to drivers based upon location analytics of a large national historical accident dataset. Employing a cadre of professional "test" drivers split in two groups – control or intervention, the authors found evidence that in-vehicle warnings about hazardous accident hotspots improved driver behavior over time. Additionally, the authors found that driver personalities played a key role in the effectiveness of in-vehicle DSS. Overall, the results confirm the importance of examining personal traits when researching interventions by DSS. This study has implications for individual drivers, automotive companies, insurers, and should also motivate researchers interested in developing lightweight, low-cost, scalable DSS for accident prevention in transportation and similar interventions in other settings such as healthcare. The implications of the study in the new age of internet-enabled devices and sensors (Internet-of-Things) also merit further research.

The last two papers of the Special Issue both examine issues in carsharing and ridesharing, within the broader context of the sharing economy. In "Moving in Time and Space - Location Intelligence for Carsharing Decision Support," Willing, Klemmer, Brandt, and Neumann have developed a DSS that helps free-floating carsharing companies resolve imbalances between vehicle supply and customer demand in central business districts in urban, metropolitan areas. Spatiotemporal demand patterns at different times of the day and different days of the week are examined for a carsharing company in Amsterdam, factoring in varied points of interest that are geographically dispersed. Sophisticated kernel density estimation and gradient boosting help identify point of interest categories that have the highest predictive power with respect to demand. Demand estimation and prediction provide decision support for the creation of carsharing pricing strategies and pricing zones. The authors evaluate their model's performance for Amsterdam and subsequently compare predicted rental densities with actual rental densities for Berlin to demonstrate generalizability of their results.

The paper "An Open-Data Approach for Quantifying the Potential of Taxi Ridesharing" by authors Barann, Beverungen, and Muller quantifies the potential of taxi-ridesharing for a large well-known dataset of taxicab trips in New York City. In the one-to-one taxi ridesharing approach that matches rides with similar start and end points, a variety of constraints – spatial constraints that measure walking distances between pickup points and drop-off points, temporal constraints governing pickup and drop-off times, and car capacity are factored in. Cost savings resulting from improved taxicab occupancy, reduction in total distance traveled, ride time, and improvements in proportion of shared rides versus individual rides were among a host of metrics that were compared by the authors for two different time periods to estimate the true potential of ridesharing. Sensitivity analysis with respect to increasing the threshold of walking between pickup/drop-off location and times is also conducted to estimate the savings potential resulting from sharing rides. As traditional transportation business models are being increasingly disrupted by ridesharing, this study provides important decision support for taxicab companies regarding competitively pricing shared rides and contending for market share with ridesharing companies such as Uber.

The papers in this Special Issue have each examined problems in which location is meaningful in the research questions themselves. Often, location is an important component of their primary research data. The contributed papers span a variety of application areas such as healthcare, entertainment, ridesharing, and transportation, and examine problems such as facility location, topic and trend analysis in social media, accident prevention, and demand estimation, demand servicing and related decision support. Tracing back to our framework of location analytics and decision support research (Fig. 1), the papers have adopted theory-based conceptual foundations in a select few cases and employed location and non-location analytics (LA & NLA) in tandem and integrated them in varying degrees to provide either predictive decision support (in several instances) or prescriptive decision support (in a couple of instances). With the advent of big data and increasingly available geographically-referenced datasets, we anticipate predictive modeling of geo-referenced phenomena of interest to DSS researchers to be on the rise. Additionally, in at least half of the papers, empirical validation has been conducted using datasets, which are structured for the most part. The paper by Lozano et al. ventures into the territory of topic modeling using unstructured big data. Impacts of decision support provided to problems examined in the papers are expected to have business value, economic, social, societal, and environmental impact, and have the potential to inform policy in urban transportation, urban planning, equitable access to healthcare, among other areas. We conclude this editorial introduction to the Special Issue with our thoughts on evolving trends in the role of location analytics and related decision support in future research and an outline of prospective research directions.

5. Trends in location analytics and decision support, gaps, and future directions

5.1. Trends in location analytics and decision support in MIS research

Location analysis has become pervasive with the advent of location-based services, cloud-based web services, mobile devices, big data, and social media. In the age of citizen science (citizens as sensors), volunteered geographic information, wearables, telematics, collaborative consumption, and the internet of things are producing vast amounts of geographically referenced data. This trend opens opportunities for location analytics methods to be combined with well-known decision-making and analytics concepts and principles including those from decision support systems, strategic IS, databases, data mining, networks, web development, and mobile design.

Concomitantly, an interesting trend observed in prior location analytics and decision support related research published in *Decision Support Systems* and a handful of articles that are part of this Special Issue is their focus on prediction. With greater availability of georeferenced data, we anticipate research into predictive modeling of geospatial phenomena, such as spatial patterns of diffusion of information, knowledge, topics, consumer trends, lifestyles, disease, crime, and customer demand, to be on the fast track. This is especially relevant due to implications for strategic, tactical, and operational decision-support for resource allocation in many sectors and industries, location-based marketing, workforce optimization and management, and critical infrastructure planning and maintenance in the event of an emergency.

We also observe an emerging trend of novel research questions to be prompted by heretofore unavailable data in many sectors and industries. This is likely to motivate the need for developing conceptual models and theories, empirical testing of associations and relationships posited by those models, and the need to define the objectives for a solution, and design, develop, demonstrate, evaluate, and communicate solutions and artifacts. This is likely to catalyze design science research in the area of location analytics and decision support, with one paper in this Special Issue hinting to this trend.

Last but not the least, research in any field is often enriched with cross disciplinary infusion of theory, concepts, and knowledge. As researchers in MIS grapple with geographically referenced phenomena and datasets, it becomes imperative to infuse and integrate traditional non-location analytical methods with spatial analytical theories, methods, and techniques. This has been witnessed in the papers of this Special Issue for the most part. Moving forward, we anticipate this trend to grow resulting in tighter integration of location and non-location analytics in DSS research.

5.2. Gaps which lead to prospective future research

Although the trends have served to advance location analytics and decision support, there are gaps in this knowledge area that remain to be addressed. One gap that has future potential is research on LA/NLA/DS which expands the variety of geographic and spatial techniques (see Section 2.3). For instance, researchers could consider decision support models that utilize Getis-Ord statistics, kriging, geographically weighted regression, spatial econometrics, local indicators of spatial association (LISA) techniques, Huff modeling, among others [2,10,22,27] which are in common use in geographic information science [23]. Another area of future potential is to continue the trend noted in Sections 2.5 and 4 of stronger integration of LA, NLA, and DS. There are synergies in doing this that can potentially lead to more powerful, efficient models and tools.

Often LA/NLA/DS research investigation has been stronger conceptually on the NLA side, with excellent explanations of optimization, statistical, and heuristic theories and framework, but limited in spatial theory. Advancements in this area might derive from enhancing and adapting existing geographic and spatial theory and combining it with the mainstream DSS theories. Another approach would be to combine several existing spatial theories that apply to decision making. For instance, in GI Science, recent effort has led to combining of the Huff retail location model, with Bass product diffusion model, and Berry hierarchical diffusion model [3,4,13,18]. The combined model can address retail decision-making in novel ways.

Research opportunities exist in the emerging research area of big data and in particular its unprecedented ability to process the rapidly expanding spatial information flows from social media, sensors, drones, satellites, and RFID-based locations to analyze how this flood of data interacts with socio-economic information at varied levels of analysis leading to distilled information kernels for predictive decision making, for example in retailing [1]. Advanced machine learning techniques, for example deep learning, that use distributed technologies, such as Apache Spark, can find research applications in analyzing big data, some of is spatially referenced. Big data sources with spatial referencing are evolving and some examples that could influence LA/NLA/DS research include Internet of Things (IOT), healthcare mobile apps, sharing economy (e.g. Airbnb, Uber), transportation (e.g. US Federal Aeronautics Administration, NY City Taxi and Limousine Commission), social media (Twitter, etc.), and drones. Big data, machine learning, and IoT can facilitate the development and implementation of innovative and disruptive business models.

Finally, LA/NLA/DS research can be expanded in the future to study industry-sector application areas that are under-researched in the DSS community and have a strong locational basis, such as utilities, insurance, oil and gas, banking, real estate, and telecommunications. Spatially-referenced data in these industries are being uncloaked and more often made available to academic researchers, as their data analysts seek to make use of R&D discoveries.

We hope the editorial brings forward more awareness of location analytics and its relationship to non-spatial analytics and decision support, major evolving trends in this area of decision support, a broad framework for LA/NLA/DS research, and gaps that offer future research opportunities. This special issue moves the needle forward on research in this area by demonstrating the value of adding location and place to decision support research and by demonstrating and elucidating rapid advances taking place on the spatial underpinnings of decision support which parallel more familiar evolving non-spatial decision-support models, analytics, and methods. Eight thought-provoking papers addressing topics as diverse as geography of online network, deleterious facility location, healthcare accessibility decision support, accident prevention using in-vehicle DSS, and spatiotemporal patterns of car- and ride-sharing follow in the remainder of the Special Issue.

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