Classifying innovation districts: Delphi validation of a multidimensional framework

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Classifying innovation districts: Delphi validation of a multidimensional framework

Abstract: Establishing innovation districts is a highly popular urban policy due to the economic, social and spatial benefits they offer to the host city. Investing on innovation districts is a risky business as there is no one-size-fit-all innovation district type. Besides, there only exists limited understanding on the varying features, functions and spatial and contextual characteristics of this new land use type. This study aims to contribute to the efforts in classifying innovation districts holistically through a multidimensional framework. The study builds on a conceptual framework developed by the authors and expands it into an operational framework that consists of numerous attributes—i.e., four dimensions (feature, function, space and context), 16 indicators and 48 measures. The framework and its attributes are subjected to validation by an panel of 32 experts through an international Delphi survey. This paper reports the process of framework development and validation. The resulting multidimensional innovation classification framework is first of its kind. It is useful in determining the key characteristics of existing innovation districts, helps in understanding what works in certain locations and what does not, and informs decisions of policymakers in investing the type of innovation districts suitable for the local context.

Keywords: innovation district; classification framework; feature; function; space use and design; knowledge and innovation economy

1. Introduction

Across the globe many cities have been developing policies to prioritise and incentivise the clustering of knowledge and innovation activities (Yigitcanlar & Inkinen, 2019). These policy efforts have become the springboard for the formation of urban knowledge and innovation spaces.

As a result of these policy efforts, a new land use type, so called ‘innovation districts’ (Esmaeilpoorarabi et al., 2018a), has emerged (Metaxiotis et al., 2010; Morisson & Bevilacqua, 2019). Innovation districts are defined as “geographic zones that cluster and connect leading-edge anchor organisations (universities, R&D centres) and innovative firms with supporting and spin-off entities, business incubators, mixed-use housing, office and retail space, high-tech amenities, and high-quality public transportation, among other perks” (Katz & Wagner, 2014, p.1).

Owing to the local contextual factors, innovation districts differ in terms of their features, functions and spatial characteristics. This is to say, there exists a rich variety of innovation districts throughout the globe. Existence of such variety makes it harder for urban administrations to decide on the kind of innovation district to invest on (Pancholi et al., 2020). This calls for a holistic classification that detail the key attributes or characteristics of innovation districts.

So far, a number of scholars have attempted to classifying them (see Table 1 for the lists of these attempts). Nonetheless, these classifications were based on only limited features, functions or spatial characteristics. Among these classifications, the most popular one is developed by Markusen (1996). She classified innovation districts as follows: “(a) Marshallian district; (b) Hub-and-spoke district; (c) Satellite platform district, and; (d) State-anchored district” (Yigitcanlar et al., 2020, p.2). This classification was based on ‘firm configuration’, ‘internal or external orientation’ and ‘governance structure’, which only partially covered feature and function attributes, and totally excluded spatial attributes.

A thorough review of the literature, by Yigitcanlar et al. (2020), confirmed that there is no innovation district classification framework that holistically covers features, functions and spatial characteristics. This limitation prompts the question of ‘How can innovation districts be holistically classified by considering their multidimensional characteristics?’ This study, hence, aims to contribute to the efforts in classifying innovation districts holistically through a multidimensional framework—by developing and validating a holistic classification framework based on the key features, functions and spatial characteristics of innovation districts.

The study first identified the potential attributes—i.e., dimensions, indicators, and measures—of a classification framework through a comprehensive review of the literature. Then, the Delphi study method was employed to determine the adequacy and accuracy of the proposed attributes of the framework. The significant output of the Delphi study, in which a total of 32 international multidisciplinary experts participated, is the multidimensional classification framework of innovation districts. As a classification tool, the developed framework will contribute to our understanding on how innovation districts can holistically be classified.

Following this introduction, the rest of the paper is organised as follows. Section 2 provides a review of the literature concerning innovation districts and their classification attempts. Section 3 presents the methodological approach of the study including the conceptual framework developed by Yigitcanlar et al. (2020), its expansion into a fully-fledge operational framework, and validation of the framework by an international panel of 32 Delphi experts. Section 4 reveals the results of the Delphi study, and shows the revised and finalised framework. Section 5 closes the paper with a discussion and final remarks.

2. Literature Background

Innovation district is an emerging land use type, where also referred to as urban model of innovation (Millar & Choi, 2010; Wagner et al., 2019) that has become a global phenomenon for many cities in recent years primarily due to the agglomeration benefits attached with it. The term innovation district is used interchangeably with 'high technology district' (Forsyth, 2014), 'science and technology park' (Diez -Vial & Olmos, 2015), 'knowledge community precinct' (Esmailpoorarabi et al., 2020b), 'innovation and cultural districts' (Jones, 2017), 'innovation precincts' (Esmaeilpoorarabi et al., 2018b), 'knowledge and innovation spaces' (Pancholi et al., 2019) and the likes—that are mostly inner-city and suburban mixed-function land uses (Yigitcanlar et al., 2020). In a nutshell, innovation district is the nexus of knowledge-based urban development (Yigitcanlar & Dur, 2013; Yigitcanlar & Inkinen, 2019) that promotes sustainable innovation.

Classic examples of innovation districts include Silicon Valley in the US and Sophia-Antipolis in France (Pancholi et al., 2015; Esmailpoorarabi et al., 2020a). The modern examples are Singapore's One-North, and Spain's 22@ Barcelona Innovation District. Whilst the former innovation districts were developed for single-purpose use within enclosed district walls based on closed innovation systems design (Yigitcanlar et al., 2020), the more contemporary ones are designed and developed as boundaryless environments and mixed land uses encouraging open innovation systems with strong social networks (Van Widen & Carlvaho, 2016; Jones, 2017; Wagner et al., 2019; Yigitcanlar et al., 2020). The new generation innovation districts prosper as the growth nodes for their host cities to achieve the promised agglomeration benefits that comes in forms of economic, technological, sociocultural and environmental outcomes (Yigitcanlar et al., 2017; Pancholi et al., 2018). They also provide a mixed-use cyber environment for knowledge workers and other users within the district (Yigitcanlar et al., 2015; Pancholi et al., 2019), which encourages networking and collaboration amongst the users, and hence contributes to the success of innovation activities (Kovacs & Petruska 2014; Wagner et al., 2019).

There is evidence in the literature on the contributions that both sustainable innovation and knowledge-based development bring to smart places (i.e., cities, districts, neighbourhood, ecosystem). The contributions include, but not limited to, environmental innovation (i.e., innovations focused on environmental goals and motivations such as facilitating sustainable development) ─ firms' productivity is positively affected by environmental knowledge (Aldieri et al., 2020). Similarly, "digitalisation of systems of innovation makes an open system of innovation result in the creation of cyber-physical systems that collaboration networks, platforms, data and analytics sustain innovation processes, capabilities and performance" (Panori et al., 2020, p.2).

Cities mainly develop innovation districts primarily for the agglomeration benefits that come in forms of economic, technological, sociocultural and environmental outcomes (Yigitcanlar et al., 2017; Pancholi, et al., 2018). Despite their popularity, not all innovation districts are successful in delivering the expected agglomeration benefits (Yigitcanlar & Inkinen, 2019). This may be due to the lack of state government's early interest and participation (O'Mara, 2004), low level of private sector research and development, and lack of collaboration amongst firms (Dodgson et al., 2011; Yigitcanlar

& Bulu, 2016; Yigitcanlar et al., 2019). These reasons, coupled with excessive changes in forms of emergence of new key players (knowledge and creative workers), population movements, firms clustering patterns, and job creation taking place in cities overtime continually challenge policymakers to provide solutions (Carrillo et al., 2014). In this context, a potential solution is to identify the main characteristics of existing innovation districts and holistically classify them. Such classification will inform related authorities to decide on which type of innovation district to develop in which location (Yigitcanlar et al., 2020).

Despite being the nexus of knowledge and innovation economy, the key functional and spatial characteristics of innovation districts vastly vary due to their differing local contextual factors. Consequently, we observe a rich variety of innovation districts (Forsyth, 2014; Hsieh et al., 2014; Hawken & Han, 2017). This makes it difficult to holistically classify them with existing approaches. Most innovation districts have some common characteristics—in terms of general economic, spatial, social networking assets, governance and funding support (Katz & Wagner, 2014; Wagner et al., 2019)—, they are distinctive in possessing specific functions, features and spatial qualities. Table 1 lists studies on the common types of innovation districts and their classification categories. All classification categories listed in Table 1 concern either hard (tangible) or soft (intangible) factors. While hard factors are related to 'place focus', soft factors cover 'people focus' (Esmaeilpoorarabi et al., 2018a). Although both hard and soft factors play a fundamental role in classification of innovation districts, previous research has dominantly focused on hard factors.

Table 1: Innovation district types and classification categories (Yigitcanlar et al., 2020, p.5)

Study	Type	Classification category	Factor
Roelandt et al. (1996)	(a) Industrial clusters based on their specialisation patterns	Function	Hard
	(b) Industrial clusters based on their innovation characteristics	Characteristics of knowledge activities	Hard
		Formation process	Hard
		Behaviour (i.e., competition and collaboration)	Soft
Markusen (1996)	(a) Marshallian district	Firm configuration	Hard
	(b) Hub-and-spoke district	Internal versus external orientation	Hard
	(c) Satellite platform	Governance structure	Hard
	(d) State-anchored districts		
Clark et al. (2010)	(a) Type 1: Marshallian innovation districts	Patent data	Soft
	(b) Type 2a: Hub-and-spoke innovation district	Regional resilience	Hard
	(c) Type 2b: Satellite platform innovation district		
Forsyth (2014)	(a) Corridors	Location	Hard
	(b) Clumps	Physical scale of development	Hard
	(c) Cores	Level of physical planning, and urban design	Hard
	(d) Comprehensive campus		
	(e) Technology sub-divisions		
	(f) Scattered technology sites		
Katz & Wagner (2014)	(a) Anchor plus	General observations	Hard
	(b) Re-imagined urban areas		
	(c) Urbanised science park models		
NSW-IPC (2018)	(a) Health and education innovation district	Sectors	Hard
	(b) Innovation precincts around universities	Locality setting	Hard
	(c) Innovation precincts around a major asset		
	(d) Inner city innovation locations		
SGS (2020)	(a) Services innovation district	Sectors	Hard
	(b) Multi-sector design driven innovation district	Business activity type	Hard
	(c) Science innovation district		
	(d) Manufacturing innovation district		
	(e) Regional resource innovation district		

In one of the earlier studies, Roelandt et al. (1996) used function, characteristics of knowledge activities, formation process, behaviour in competition and collaboration as the main classification categories and identified two innovation clusters based on either their specialisation patterns or innovation characteristics. In the same year, Markusen (1996) used the classification categories of firm configurations, internal versus external orientation and governance to identify four types of innovation districts: (a) Marshallian; (b) Hub-and-spoke; (c) Satellite platform, and; (d) State-anchored. After a while, patent data and regional resilience were added to Markusen's categories by Clark et al. (2010), which resulted in the rebranding of the innovation districts. Four years later, Forsyth (2014) employed location, level of physical planning, and urban design to classify innovation districts. The study identified six types of innovation districts as presented in Table 1. Since 2014 researchers have been using sectors, business activity types, and locality as the predominant classification categories (e.g., NSW-IPC, 2018; SGS, 2020). Evidently, the classification categories have evolved over time, but, none of these studies have attempted to holistically classify these districts.

Most recently, Yigitcanlar et al. (2020) offered a conceptual framework for classification of innovation districts as illustrated in Figure 1. This framework was developed based on a comprehensive literature review on how to develop a classification framework guideline (Collier et al., 2012) and the main characteristics of innovation districts identified in the literature—i.e., function, feature, space use and context. These four dimensions together with their indicators forms the cornerstone of developing a classification framework for innovation districts. The specifics and expansion of this conceptual framework are presented in the next section.

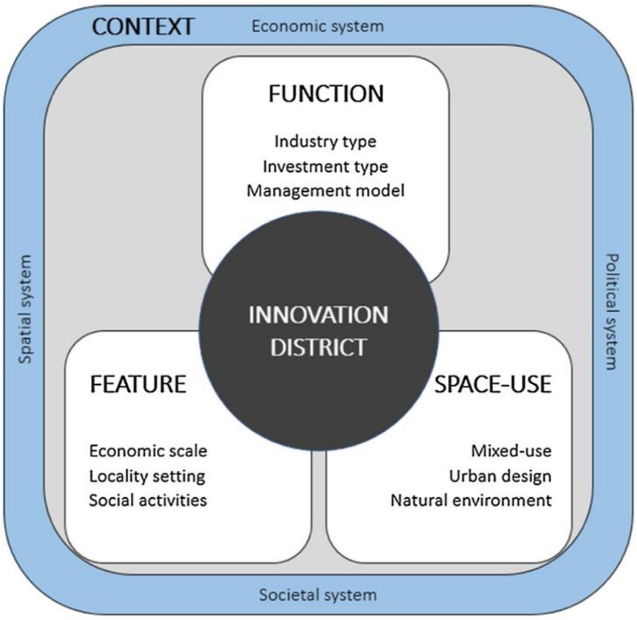

Figure 1: Initial conceptual framework for innovation district classification (Yigitcanlar et al., 2020, p.10)

3. Empirical Investigation

3.1. Methodology

This study adopts the conceptual framework (Figure 1) developed by Yigitcanlar et al. (2020), which is based on the review of 58 scholarly articles to identify the most cited indicators relating to classification of innovation districts. The study then expands the conceptual framework into the proposed classification attributes (presented in Table 2) after additional peer-reviewed articles and other relevant sources are consulted for appropriate measures and parameters to use. A variety of approaches can be used to identify initial attributes (i.e., dimensions, indicators, measures) for developing a classification framework. This study employed the most popular approach—the literature review method, then made recommendation to the experts for evaluation of each attribute's suitability and adequacy (Ameyaw & Chan, 2015; Kiba-Janiak, 2016; Esmaeilpoorarabi et al.2018a).

Table 2 provides a detailed descriptions of the potential attributes to develop a holistic classification framework for innovation districts, where 'indicators' are the key measurable elements selected for each dimension (e.g., investment type, management model, locality setting), and the ‘measures’ describe each of the indicator’s performance to classify innovation districts. Particularly, the top indicator for ‘function’ dimension is ‘industry type’, which identifies the dominant business activity within an innovation district. The measures defined for industry type are: High-tech business intensive, creative business intensive, and business support service intensive. At this stage, the recommended attributes are identified as potentials, therefore the experts were encouraged to suggest any additional or replacement attributes that they deemed important and need to be included or otherwise excluded in the classification framework.

Table 2: Initial dimensions, indicators and measures of innovation district classification

Dimension	Indicator	Description	Measure
Context	Economic system	Macroeconomic progress of the city (e.g., monetary, and fiscal performance to maintain stability of economic growth)	▪ High-performance economic system ▪ Mid-performance economic system ▪ Low-performance economic system
	Political system	Political progress of the city (e.g., political institution effectiveness, accountability, transparency, participation)	▪ High-level governance effectiveness ▪ Mid-level governance effectiveness ▪ Low-level governance effectiveness
	Societal system	Societal progress of the city (e.g., equality, age structure, participation in cultural/community activities, tolerance, diversity)	▪ High-level societal equality ▪ Mid-level societal equality ▪ Low-level societal equality
	Spatial system	City-wide spatial-environmental qualities (e.g., physical environment, spatial conditions, physical urban development)	▪ High-quality spatial environment ▪ Mid-quality spatial environment ▪ Low-quality spatial environment
Function	Industry type	Dominant business activity operating within the innovation district	▪ High-tech business intensive ▪ Creative business intensive ▪ Business support service intensive
	Investment type	Principal support and funding body for the development of the district	▪ Public-private partnership driven ▪ Private sector driven ▪ Public sector driven
	Management model	Management model of the innovation district’s properties and activities	▪ District-wide body corporate ▪ Building-base body corporate ▪ No body corporate
Feature	Economic scale	Skilled employment outcome of the district activities	▪ High-level skilled employment ▪ Mid-level skilled employment ▪ Low-level skilled employment
	Locality setting	Location of the district within the metropolitan area	▪ Urban ▪ Suburban ▪ Ex-urban
	Sociocultural places/activities	Public places and socio-cultural activities within the innovation district	▪ High-quality public/sociocultural places ▪ Mid-quality public/sociocultural places ▪ Low-quality public/socio cultural places
Space Use	Land use	Main land use types of the innovation district	▪ For work-learn-play-live uses ▪ For work-learn-play uses ▪ For work use only
	Built environment	Urban and architectural design encouraging open innovation system within the innovation district	▪ High-level design qualities (e.g., open design) ▪ Mid-level design qualities (e.g., semi open design ▪ Low-level design qualities (e.g., close design)
	Natural environment	Aesthetic qualities of urban green and blue spaces within the district - significant natural features- e.g., >50% water coverage, >50% tree cover, good view/vista points)	▪ High presence of green and blue spaces ▪ Moderate presence of green and blue space ▪ Low presence of green and blue space

Following other similar studies (Von der Gracht, 2012; Mafi et al., 2015; Esmaeilpoorarabi et al., 2018a; Perveen et al., 2018), a Delphi study method was employed to validate the proposed classification attributes in Table 2. Experts with multidisciplinary backgrounds from both Australia and overseas were consulted to validate the proposed dimensions, indicators and measures.

Subsequently, the study developed a multidimensional operational classification framework, which can holistically classify the variety of innovation districts. The rationale for employing Delphi study as the validation method for the proposed classification attributes is as follows. First, the previous research confirms that there is limited empirical research on investigating and developing a holistic classification framework. Second, the Delphi study is suitable for circumstances where there is limited resources and documents (Ruppert & Duncan, 2017; Esmaeilpoorarabi et al., 2018).

3.2. Delphi Method

The Delphi method is widely used and accepted by researchers for obtaining experts opinion on a topic within their domain of expertise. The method was introduced by the Rand Corporation in 1950 (Dalkey & Helmer, 1963; He et al., 2016). "The technique is designed as a group communication process, which aims to achieve a convergence of opinion on a specific real-world issue" (Hsu & Sandford, 2007, p.1). Scholars including Ruppert & Duncan (2017) and Rust (2017) refer to this technique as "a reiterative systematic policymaking process, which utilises a series of anonymous questionnaires to collect expert opinions" (Esmaeilpoorarabi et al., 2018a, p.473). The Delphi method has four distinct features: (a) Anonymity─ a group of experts (panellists) are selected to participate on an online questionnaire about a specific research topic. The process is anonymous to avoid social pressure and potential bias in responses; (b) Iteration─ the process comprised of several rounds of enquiry which subsequent rounds are designed as feedback process; (c) Controlled feedback ─a group summary of responses for each round is presented to the experts in the next rounds to allow and encourage revisions of their initial judgements until consensus is achieved, and; (d) Statistical group response─ the Delphi method produces two outcomes, namely the analytical statistics and the consensus levels (von der Gracht,2012; Barnes & Mattsson, 2016; Junger et al. 2017).

Our study executed the Delphi method in the following manner.

Selection of the experts: Three main principles are followed in selecting experts for our Delphi study. First, the experts are selected from both the academic and professional sectors to ensure both theory- and practice-oriented views are gathered. Second, the experts are selected from different geographical locations, including Europe, North America, Latin America, Asiatic region, Pacific region, and the Middle East, to ensure wider coverage/validity of opinions (Ruppert & Duncan, 2017). Third, the experts are selected from a diverse, but related disciplinary areas "to provide a heterogeneous landscape to the research" (Esmaeilpoorarabi et al., 2018a, p.475). The disciplinary areas include: Architecture and urban design; Economics and business; Communication and information technology; Sustainability; Geography, planning, and development (specifically innovation districts); Creative industries and cultural policies; Property and real-estate, and; Public policy and administration. Furthermore, two key eligibility criteria are employed in the selection of the Delphi survey experts: (a) Academics must be employed in an academic institution, and have publications on innovation district or related topic in international peer-reviewed journals in past five years (Meijering et al., 2015); (b) Professionals must be employed in either a public or private organisation, and have been actively involved in the planning, design, development or management of an innovation district during the past five years. These eligibility criteria ensured the quality of the sample pool and reliability of expert inputs (Esmaeilpoorarabi et al., 2018a).

Expert profiles: After checking the experts' profiles regarding their disciplinary areas and geographical locations, it is observed that the two most prevalent groups of experts are specialised in urban planning and real-estate (41%), and architecture and urban design (22%) disciplines. The prevalent groups are actively participating in the design, planning, development, and management of innovation districts. On the lower end, social sciences, business, and communication studies equally share the remaining 38%. The lower representation is because they have a focus on limited aspects of the innovation districts (Esmaeilpoorarabi et al., 2018a). In terms of geographical distribution, 31% of the experts were from Europe; 22% from the Middle East; those from Latin America and Pacific region have equal shares of 19%; 6% from Asiatic region, and; The remaining 3% from North America (3%). Hence, a heterogeneous sample of experts is assembled that represents a rich variety of views. The experts' invaluable inputs provided critical insights in the selection of the dimensions, indicators, measures, and parameters to finalise the classification framework. Furthermore, having an adequate number of experts in the study is equally important. For homogenous samples, 10-15 experts are said to be reasonably adequate; nonetheless, for heterogeneous samples 30-50 experts are required (Ameyaw & Chan, 2015; Mafi et al., 2015; Nourouzian-Maleki et al., 2015; Alawadi & Dooling, 2016). As the present study required a heterogeneous sample, we targeted a minimum of 30 experts to participate, and invited a total of 113 experts to ensure the minimum target of 30 is achieved.

Number of rounds: To date, there has been no consensus among scholars regarding the number of rounds required to reach a consensus in the survey. Instead, the number of rounds depend on when consensus is reached by the participants (Esmaeilpoorarabi et al., 2018a). Whilst some studies recommend two rounds (Gigovic et al., 2016; Soria-Lara & Banister, 2017), or three rounds (Jordan & Javernick-Will, 2013; Singhal et al., 2013), others recommend more than three rounds until a consensus is reached (Ruppert & Duncan, 2017). Our study conducted the Delphi survey in two rounds that is when the consensus was achieved.

Response rate: In the first round 32 international experts of multidisciplinary areas validated the proposed dimensions, indicators, measures, and their parameters. At the end of Round 1, completed questionnaires are returned to the researchers to collate, edit, then results are summarised and incorporated into the questionnaire for the next round of survey. By doing so, each participant was informed of the general viewpoints and underlying reasons. Thus, the feedback process allowed and encouraged experts to revise their initial judgments (Esmaelipoorarabi et al., 2018a). In the second round, only 17 of the 32 experts from Round 1 participated, in which a similar process was followed in collating and editing of the completed questionnaires.

Both qualitative and quantitative analyses were carried out using the data extracted from the experts' responses. Whilst the qualitative analysis employed the experts' suggestions and comments for possible revision of the proposed frameworks, the quantitative analysis employed the use of statistical analysis to determine the central tendency and dispersion measures, to evaluate reliability of the questionnaire, internal homogeneity, and consistency of opinion among experts. In addition, the consensus level among experts was determined using the report generated from the Key Survey Tool, which is an enterprise survey platform.

3.3. Delphi Survey

The proposed classification attributes, presented in Table 2, formed the Delphi survey questionnaire. As the survey's aim was to collect both quantitative and qualitative data, Likert-scale and open-ended questions were used. "Likert-scale questions were used to measure the suitability/adequacy of the recommended dimensions, indicators, and measures; to assess the level of consensus among experts; and generate the mean weightings of expert's scores, whilst the open-ended questions allowed the experts to provide rationales for their scores" and make suggestions for any renamed or new dimensions, indicators, measures, and parameters (Esmaeilpoorarabi et al., 2018a, p.475). Following the other relevant studies (Kiba-Janiak, 2016; Soria-Lara & Banister, 2017), our study applied a 11-point scale (from 0-no, 1-strongly disagree to 10-strongly agree) on the following bases. Firstly, it provides respondents more selection options for rating then a limited lower scale (e.g., a 5-point scale). Secondly, it provides multi-categories for calculating consensus levels—i.e., 0-2 (strongly disagree), 3-4 (disagree), 5 (neutral), 6-7 (agree), 8-10 (strongly agree)—and makes reporting easier.

The Delphi survey process commenced Round 1 with an invitation email sent initially to 78 potential experts and then biweekly reminder emails were sent out. After two weeks, only 29% (n=23) experts completed the survey, which was below this study's minimum sample size target of 30. A third reminder was sent to experts yet to complete, and new invitation emails were sent to additional 35 experts with intention to achieve the sample target of 30. This increased our potential participants from 78 to 113 experts. The survey expiry date was then extended for another week to achieve more responses, accordingly the survey completed with a total of 32 experts. As the number of response (n=32) was within the range of acceptable sample size of 30-50 participants (Ameyaw & Chan, 2015; Mafi et al., 2015; Nourouzian-Maleki et al., 2015; Alawadi & Dooling, 2016), Round 1 was then closed. In Round 2, email invitations were sent the to 32 experts who already completed Round 1 survey. Out of the 32 experts invited to participate in Round 2 only 17 (or 53%) completed the survey. According to the authors, this is an acceptable response rate on the premise that the response is over half (>50%) of the total invited experts and consistent with the respond rates of similar studies listed in Table 3.

Table 3: Sample size used in Delphi studies (Perveen et al. 2017, p.10)

References	Field of study	Round 1 sample size	Round 2 sample size	Response rate (%) between rounds
Hayati et al. (2013)	Land use and transportation	9	9	100
Spickermann et al. (2014)	Urban planning	57	39	68
Musa et al. (2015)	Urban sustainability	34	31	91
Kaufmann (2016)	Land use	18	10	56
Howell et al. (2016)	???	30	26	87
Perveen et al. (2017)	Urban sustainability	29	29	100
Esmaeilpoorarabi et al. (2018)	Innovation district	43	34	79

3.3.1. Selection of Indicators (Round 1)

The questionnaire was distributed through the online Key Survey tool, which comprised of an introduction of the project, research aims and objectives, the conceptual framework (Figure 1) and the proposed classification framework (Table 2) and questions. Descriptions of the recommended indicators and their measures were also provided to avoid misunderstandings among experts that may affect their scoring in the survey. The experts were required to score the importance of four dimensions, 13 indicators and 39 measures in classification of innovation districts. For example, the experts were asked to score between the four context indicators and which indicators they think are more important in classifying innovation districts. In total, 13 open-ended questions were included to obtain experts' opinions on the adequacy and accuracy of the recommended dimensions, indicators, and measures. After Round 1, both the conceptual and the proposed indicator frameworks were modified based on the results of the qualitative and quantitative analysis. The duration of the survey was approximately three months (September-November 2020) for both rounds.

3.3.2. Selection of Indicators (Round 2)

In Round 2, a similar process employed in the previous round was followed to distribute the questionnaire. However, the content of the questionnaire was reformatted to include instructions for Round 2 requirement, the revised conceptual framework (see Figure 2) and the classification attributes (see Table 4) based on Round 1 feedback. As both the categories of 'dimension' and 'indicators' achieved consensus in Round 1, the researchers agreed that it was not necessary for the experts to reassess their initial scores except for the renamed or new dimension, indicators and measures. The attribute that did not achieve consensus in Round 1 was 'measures' thus all the measures needed reassessment by the experts in Round 2. Furthermore, the experts strongly recommended to replace subjective measures with objective measures and include parameters for measures. We incorporated these suggestions in the formulation of Round 2 questions.

A total of seven questions were formulated, three relating to rating the importance of the attributes of concern (i.e., those which fail to achieve consensus, renamed or new addition) in classification of innovation districts. For example, the experts were asked to score on a 11-point Likert-scale (0-10), how much they agree on the name-change of 'space use' to 'form' under the dimension category. Similar question type was used for the 'indicator' category. However, the question for 'measures' category was slightly different as the experts were required to review all their initial ratings in Round 1 (including any name change or new additions) by indicating the importance of these measures on a 11-point Likert scale (0-10). Also, a summary table of consensus achieved/not achieved in Round 1 was provided for the experts' information. The other three questions are relative to the former questions which required the experts to provide an overall rationale for their scores and the final question is for the experts to make any general comments.

After a revision, ‘firm size classification’ was added as the fourth indicator to function dimension with appropriate measures. Likewise, ‘human capital’ was added to feature dimension and, ‘space design’ and ‘urban green-blue infrastructure’ (renamed for natural environment) were added to space design and use dimension. The revised conceptual framework displayed in Figure 2 maintained the initial four dimensions, but the number of indicators increased from 13 in Round 1 to 16 in Round 2, and similarly the number of measures increased from 39 in Round 1 to 48 in Round 2. Detailed descriptions of these attributes are illustrated in Table 4.

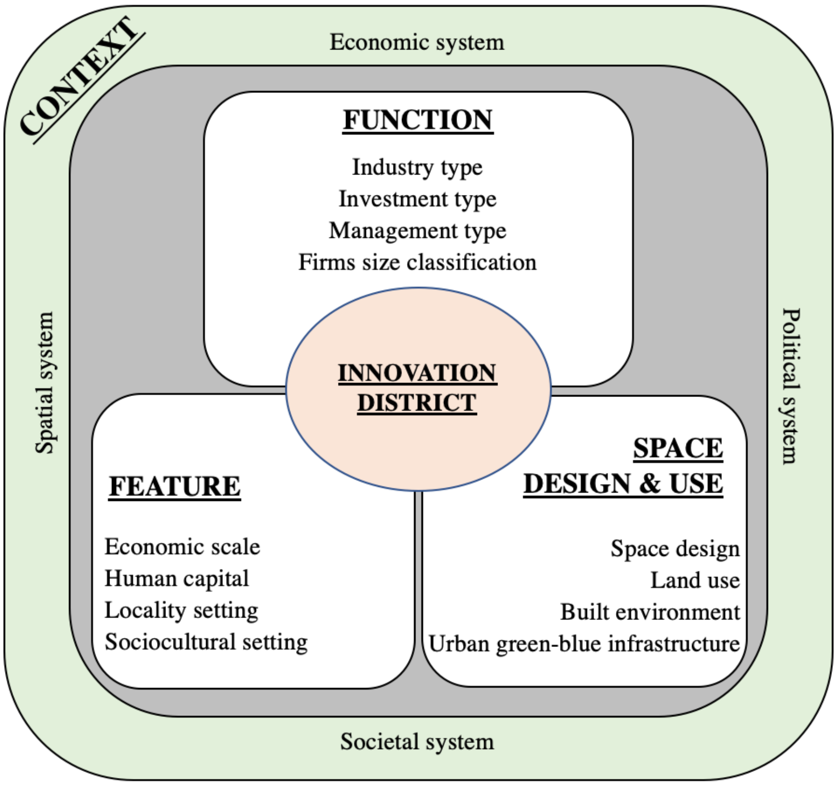

Figure 2: Revised conceptual framework of innovation district classification

Table 4: Dimensions, indicators and measures of innovation districts classification (revised after round 1)

Dimension	Indicator	Description	Measure
Context	Economic system	Macroeconomic progress of the city (e.g., monetary, and fiscal performance to maintain stability of economic growth)	▪ Leading economic performance ▪ Moderate economic performance ▪ Low economic performance
	Political system	Political progress of the city (e.g., political institution effectiveness, accountability, transparency, participation)	▪ Leading governance effectiveness ▪ Moderate governance effectiveness ▪ Low governance effectiveness
	Societal system	Societal progress of the city (e.g., diversity, tolerance, equality, age structure, participation in cultural/community activities	▪ Leading social assets ▪ Moderate social assets ▪ Low social assets
	Spatial system	City-wide spatial layout and architecture qualities (e.g., physical environment, spatial conditions, physical urban development)	▪ High quality spatial design ▪ Moderate quality spatial design ▪ Low quality spatial design
Function	Industry type	Dominant business activity operating within the innovation district	▪ High technology intensive businesses ▪ Creativity intensive businesses ▪ Business support services
	Investment type	Principal support and funding body for the development of the innovation districts	▪ Public-private partnership driven ▪ Private sector driven ▪ Public sector driven ▪ Public-private-community partnership driven
	Management model	Management model of the innovation district's properties and activities	▪ District-wide body corporate ▪ Building-base body corporate ▪ No management
	Firm size classification	Relative size of the firms within the innovation district (i.e., SME dominated, MNE anchored)	▪ Multinational enterprise (MNE) anchored ▪ Small and medium enterprise (SME) dominated
Feature	Economic scale	Skilled employment outcome of the innovation district activities	▪ High-level skilled employment ▪ Moderate-level skilled employment ▪ Low-level skilled employment
	Human capital	Inventory of skilled people (i.e., information about the education and skill levels of the population and the potential stock of qualified people)	▪ High-level human capital ▪ Moderate-level human capital ▪ Low-level human capital
	Locality setting	Location of the district within the metropolitan area	▪ Urban setting ▪ Suburban setting ▪ Ex-urban setting
	Sociocultural setting	Presence or availability of social amenities for public use within the innovation district	▪ High presence of social amenities ▪ Moderate presence of social amenities ▪ Low presence of social amenities
Space Design & Use	Space design	Spatial layouts design encouraging open innovation system within the innovation district	▪ Open layout design ▪ Part open layout design ▪ Close layout design
	Land use	Main land use types within the innovation district	▪ Work only ▪ Work-learn-play ▪ Work-learn-live ▪ Work-learn-play-live
	Built environment	Architectural design of built forms and functions encouraging open innovation systems, connectivity, and mobility within the innovation districts	▪ High-level design qualities (i.e., built form, function, and connectivity) ▪ Mid-level design qualities (i.e., built form, function, and connectivity)

	Urban green-blue infrastructure	Aesthetic qualities of urban green and blue infrastructure within the innovation (i.e., all natural and semi natural landscape elements that form a green-blue network)	▪ Low-level design qualities (i.e., built form, function, and connectivity) ▪ High-level presence of green or blue infrastructure ▪ Mid-level presence of green or blue infrastructure ▪ Low-level presence of green or blue infrastructure

Table 5: Dimensions, indicators and measures of innovation districts classification (revised after round 2)

Dimension	Indicators	Description	Measure
Context	Economic system	Macroeconomic progress of the city (e.g., monetary, and fiscal performance to maintain stability of economic growth)	▪ Strong economic performance ▪ Moderate economic performance ▪ Weak economic performance
	Governance system	Political progress of the city (e.g., political institution effectiveness, accountability, transparency, participation)	▪ Strong governance effectiveness ▪ Moderate governance effectiveness ▪ Weak governance effectiveness
	Societal system	Societal progress of the city (e.g., diversity, tolerance, equality, age structure, participation in cultural/community activities	▪ Strong social assets ▪ Moderate social assets ▪ Weak social assets
	Spatial system	City-wide spatial layout and architecture qualities (e.g., physical environment, spatial conditions, physical urban development)	▪ Strong spatial design ▪ Moderate spatial design ▪ Weak spatial design
Function	Industry type	Dominant business activity operating within the innovation district	▪ Technology intensive businesses ▪ Creativity intensive businesses ▪ Business support services
	Investment type	Principal support and funding body for the development of the innovation districts	▪ Multi sectors ▪ Two sectors ▪ Single sectors
	Property management	Management model of the innovation district's properties and activities	▪ District-wide body corporate ▪ Building-base body corporate ▪ None
	Company size	Relative size of the firms within the innovation district (i.e., SME dominated, MNE anchored)	▪ Multinational enterprise (MNE) anchored ▪ Large national enterprise (LNE) dominated ▪ Small and medium enterprise (SME) dominated
Feature	Skilled labour	Skilled employment outcome of the innovation district activities	▪ Strong skilled employment ▪ Moderate skilled employment ▪ Weak skilled employment
	Human capital	Inventory of skilled people (i.e., information about the education and skill levels of the population and the potential stock of qualified people)	▪ Strong human capital ▪ Moderate human capital ▪ Weak human capital
	Locality setting	Location of the district within the metropolitan area	▪ Inner city setting ▪ Suburban setting ▪ Regional setting
	Social amenity	Presence or availability of social amenities for public use within the innovation district	▪ Strong presence of social amenities ▪ Moderate presence of social amenities ▪ Weak presence of social amenities

Space Design & Use	Space design	Spatial layouts design encouraging open innovation system within the innovation district	▪ Open layout design ▪ Semi open layout design ▪ Close layout design
	Land -use mix	Main land use types within the innovation district	▪ Complex mix ▪ Mixed use ▪ Single use
	Built environment	Architectural design of built forms and functions encouraging open innovation systems, connectivity, and mobility within the innovation districts	▪ Strong design qualities (i.e., built form, function, and connectivity) ▪ Moderate design qualities (i.e., built form, function, and connectivity) ▪ Weak design qualities (i.e., built form, function, and connectivity)
	Urban green-blue infrastructure	Aesthetic qualities of urban green and blue infrastructure within the innovation (i.e., all natural and semi natural landscape elements that form a green-blue network)	▪ Strong presence of green or blue infrastructure ▪ Moderate presence of green or blue infrastructure ▪ Weak presence of green or blue infrastructure

3.4. Analysis

The Delphi method produces two outcomes, namely the analytical statistics and the consensus levels. The most common analytical statistics are the ‘central tendency measure’ (i.e., mean, median, mode) and the ‘dispersion measures’ (i.e., standard deviation, interquartile range), whilst the most common definition for consensus level is ‘percentage of agreement’ (Diamond et al., 2014; Esmaeilpoorarabi et al., 2018a). This study used mean values to calculate the level of importance of each of the ‘dimensions’, ‘indicators’ and ‘measures’ within their categories, which is appropriate for receiving feedback and calculating weights (Holey et al., 2007; Jordan & Javernick-Will, 2013; Singhal et al., 2013), and standard deviation to evaluate dispersion measures. A lower level of standard deviation (SD) and a higher mean value indicate that there is a stronger agreement among experts.

Some studies suggested that SD of experts mean scores below 1 in a 5-points Likert-scale questionnaire is accepted as a strong agreement amongst experts (Julsrud & Priya-Uteng, 2015; Perveen et al., 2018). While others suggested an SD below 2 is reasonable for a 4-5 Likert-scale questionnaire (West & Cannon, 1988; Rogers & Lopez, 2002). In addition, relating to a 10-11 points Likert-scale, Schmieldel et al. (2013) and Esmaeilpoorarabi et al. (2018a) suggested that SD of experts mean scores below 2 is reasonable. As the present study employed an interval 11-point Likert-scale (grouped into five agreement levels), it is expected that such multi-level of agreement/disagreement will cause high dispersion level amongst the experts’ mean scores. Thus, it is reasonable for the SD to be over 2 points. We applied the rule of thumb suggested in the mathematics and statistics literature to determine the appropriate SD point threshold. The rule of thumb for SD is “the maximum standard deviation to minimum standard deviation should be about 2:1 ratio. If the item (in this case attributes) does not fulfil the rule, it needs to be standardised to align with the scale” (Othman et al., 2011, p.12). Our quantitative results in Rounds 1 and 2 (see Appendices A and B) revealed the maximum SD of experts mean scores is 3.46 and minimum SD is 1.21, which does not fulfil the rule of thumb because the maximum SD of 3.46 is almost three times the minimum SD. To determine an ideal maximum SD of experts’, mean scores, a simple calculation is done by multiplying the minimum SD by two (i.e., 1.21 x 2) which resulted 2.42 points. Thus, a maximum SD of 2.42 and minimum 1.21 would meet the acceptable ratio of 2:1. Hence, we suggest the SD point threshold for experts’ mean scores for this Delphi study is 2.42. Hence, SDs below 2.42 points is considered as an indication of stronger agreement amongst experts.

Another important analysis that must be done prior to determining level of agreements is the measure of Cronbach’s alpha (α) which examines “the reliability of the questionnaire, the internal homogeneity and consistency of opinion among experts” (Esmaeilpoorarabi et al., 2018a, p.476). Typically, Cronbach’s α value is between 0 and 1. According to the previous research, α values above 0.7 indicate that the ratings are strongly associated and a value lower than 0.7 shows that they are unrelated (Hassanzadeh et al., 2014; Mafi et al., 2015). The measure of the consensus level (amongst experts) evaluates the levels of agreement based on the 11-point Likert-scale. More specifically, two levels of agreement are calculated in each round.

First, the overall agreement which is the sum of the percentage of scores for ‘agree’ and ‘strongly agree’ (Ruppert & Duncan, 2017; Sutterluty et al., 2017). Second, the specific agreement which is the percentage of scores for ‘agree’ and ‘strongly agree’ calculated separately. If the overall agreement for dimensions, indicators and measures achieves more than the majority scores (>60%), then these should be retained in the classification framework. On the other hand, the specific agreement level indicates priorities in each category. If the strongly agree scores for a dimension, indicator, or measure achieve more than majority votes (>60%), then these are ranked as high importance in the related category (Kaufmann, 2016; Perveen et al., 2018).

Lastly, stability tests on experts’ responses between the two rounds were carried out using both Kendall’s coefficient of concordance (W) and the coefficient of variation (CV) (He et al., 2016; Kiba-Janiak, 2016; Esmaeilpoorarabi et al., 2018a; Perveen et al., 2018). Kendall’s W calculates only the “mean values and percentage of overall agreement among continuous rounds” excluding the “level of agreements between participants", hence, Kendall's W >0.5 indicates "there is stability of mean scores and consistency of expert's judgments between the survey rounds" (Esmaeilpoorarabi et al., 2018a, p.476). Any further rounds will not make a difference to the stability results already reached. Likewise, changes in the CV value between two survey rounds can be used to measure stability (Dajani et al., 1979). If the percentage change in CV value between two rounds is less than 15%, the stability of consensus is achieved and the Delphi survey is completed (Scheibe et al., 2002).

3.4.1. Qualitative Analysis

Round One: In the qualitative analysis, each of the 32 experts rated four dimensions, 13 indicators, and 39 measures, resulting in 56 responses overall. There were more than 300 comments made by the experts through open-ended questions, which mainly focused on: (a) Expert's rationale for the scores and recommendations for additional, new or replacement of the dimensions, indicators, and measures, and; (b) Comments on which of the dimensions they think is important in classifying innovation districts. Using 'eyeball' technique to summarise the experts comments, majority (74%) of the experts think the dimensions 'function, 'context', and 'feature' are equally important then 'space-design' (12%) while only 14% say all four dimensions are equally important in the classification of innovation districts. As for indicators, one expert suggested to rename 'industry type' as 'creative industry type', another suggested 'social/societal asset' to replace 'societal equality'. However, the most noteworthy comment was on 'measures' where majority of the experts preferred using objective measures then the subjective ones recommended. In general, the experts preferred additional information or elaboration on the definition of the measures for further clarification. After a thorough consideration of the expert's inputs, both the conceptual and classification frameworks for the innovation districts were revised. Figure 2 and Table 4 present the qualitative analysis of Round 1.

Round Two: A similar process applied in Round 1 for qualitative analysis was also followed in Round 2. From the 32 experts invited, only 17 experts responded and re-assessed one dimension, five indicators and 43 measures, resulting a total of 49 responses. More than 90 comments were made by the experts through open-ended questions which focused again on their rationale for scores given and any further recommendations and comments. Some of the experts reiterate their initial suggestions to use objective instead of subjective measures. There were also additional suggestions for some renamed and new indicators, measures, and parameters which the researchers agreed to accept only the most relevant ones instead of conducting a Round 3 survey. Significant changes were made to all the 'high-mid-low measures' (subjective measures) to 'strong-moderate-weak' (objective measures). Indeed, the decision to not conduct a Round 3 survey was also supported and confirmed by Round 2 quantitative analysis results (as will be discussed below). Consequently, the classification attributes, particularly 'measures' category was further revised as illustrated in Table 5.

3.4.2. Quantitative analysis

Round One: The quantitative analysis is based on the expert's rating on a 11point Likert-scale (i.e., 0-10) in Round 1 of the importance of the recommended attributes to classify innovation districts. First analysis was done to test the reliability of the quantitative data derived from the experts' responses. The calculated Cronbach's alpha (α) was 0.962, which is above the minimum value of 0.7 and indicates there is internal consistency and reliability of data collected. Second, analysis of mean values, SDs and levels of agreements within each category was calculated as discussed below. An aggregate summary of mean value, SD, and overall and specific agreements calculations are provided in Appendix A. The SDs for expert's mean scores on all the 'dimensions' and 'indicators' calculated are below the threshold of 2.42 points which suggest that there is convergence and reliability in responses for the proposed dimensions and indicators. Nevertheless, almost 54% (30/56) of the recommended measures (highlighted in grey in Appendix A) had SDs above 2.42 points, indicating a weaker agreement amongst the experts.

In terms of overall agreement, all the proposed dimensions and indicators reached a consensus with an overall agreement of more than 60%, which indicated that dimensions and indicators are crucial for forming the innovation district classification framework and these were maintained to be used in Round 2 survey. Although the literature suggested that 50% is the minimum acceptable consensus level (Zeeman et al., 2016; Esmaeilpoorarabi et al., 2018a), this study adopted a higher consensus level of 60%. The highest overall agreement (highlighted in blue-Appendix A) was in the 80-94% range and the lowest agreement ranged from 60% to 78%.

In terms of specific agreement (highlighted in light blue in Appendix A) 43% (24/56) of the overall dimensions, indicators, and measures achieved consensus. The weak consensus among the experts could possibly be due to the missing additional information on parameters and measures as pointed out by some of the experts in the comments section.

The second-round survey, therefore, aimed to improve consensus for both the overall agreement and the specific agreement for all the dimensions, indicators, and measures that are scored below the consensus level of 60% in Round 1. Generally, improvements in both agreement levels are expected to positively improve the relative SDs of experts' mean scores.

Round Two: Discussion on Round 2 quantitative analysis hereafter is focused on the changes between the two survey rounds in terms of: (a) The overall agreement, and; (b) The SD of expert's mean scores.

In terms of percentage change in the number of 'agreements' for all attributes, the specific agreement increased by nine percentage points, from 42.86% in Round 1 to 52.17% in Round 2, while the overall agreement increased by almost 14 percentage points, from 73.21% in Round 1 to 86.96% in Round 2. Overall, the percentage for 'specific agreement' highlighted in light blue was slightly more than half (52%) of the total dimensions, indicators and measures which is acceptable. However, despite 87% of all the categories achieved an overall agreement, it appeared that there is still inconsistency in experts' opinions as some categories such as 'Form', achieved an overall agreement yet had a SD over the threshold of 2.42 points. Further analysis confirmed that such a case (as in 'form') will not negatively affect finalising of the classification framework as the calculated value of Cronbach's α for Round 2 was 0.956, indicating that there is a good overall consistency in expert opinions.

Concerning the SDs in expert's mean scores, the results revealed that the number of attributes with SDs higher than the threshold of 2.42 points reduced significantly by 27 percentage points, from 54% in Round 1 to 27% in Round 2 Confirming that a considerably lower SD increased the overall level of consensus in Round 2 survey (see Appendix B for the calculations).

Finally, the tests for stability between the two survey rounds revealed Kendall's W was 0.785 for the mean and 0.919 for overall agreement. Both are above the 0.5 cut off mark. Further, CV calculation changes between the two rounds was lower than 15%. These results confirmed stability and consistency of experts' judgement between the two survey rounds. Consequently, as these results met the above-mentioned stop criteria for Delphi studies, the researchers decided to conclude the survey at the end of Round 2.

4. Results

4.1. Response Rates and Expert Profiles

To ensure consistency with the above-defined three principles for selection of experts (Section 3.4), their disciplinary areas and geographical locations were examined. The two most prevalent groups of experts were specialised in urban planning and real estate (41%) and architecture and urban design (22%) disciplines. These two groups are actively involved in the planning, design, development, and management of innovation districts. Experts in social sciences, business, and communication studies equally share the remaining 38%. The lower representation is because they focus on limited aspects of the innovation districts (Esmaeilpoorarabi et al., 2018a). In terms of geographical distribution, 31% of the experts were from Europe; 22% from the Middle East; those from Latin America and Pacific region have equal shares of 19%; 6% from Asiatic region, and the remaining 3% from North America (3%). These figures confirmed a heterogeneous sample of experts and a fair range of opinions from diverse experts who are globally represented. The experts' invaluable inputs provided critical insights in the selection of the dimensions, indicators, measures, and parameters to finalise the classification framework.

4.2. Consensus Level and Selection of Indicators

4.2.1. Round 1

In the qualitative analysis, each of the 32 experts rated 4 dimensions, 13 indicators, and 39 measures. More than 300 comments were received through open-ended questions, mainly focusing on experts' rationale for the rating scores and recommendations for new or replacement of the dimensions, indicators, and measures. For example, some experts believed that 'function' and 'feature' are the most important dimensions, while others suggested 'space-use' and 'feature', and few of them opined that all four are equally important. As for indicators, one expert suggested to rename 'industry type' as "creative industry type", another suggested replacing 'societal equality' with "social/societal asset". However, the most noteworthy revision was in 'measures' where majority of the experts preferred using objective measures rather than the subjective ones recommended. In general, the experts preferred additional information or elaboration on the definition of the measures for further clarification. After a thorough consideration of the expert's inputs, both the conceptual and classification frameworks for the innovation districts were revised. Figure 2 and Table 3 present the result of qualitative analysis of Round 1.

A further analysis was conducted to test the reliability of the quantitative data derived from the experts' responses. First, the Cronbach's alpha (α) was calculated as 0.962, above the minimum value of 0.7, which indicates a high level of internal consistency and hence reliability of data. An aggregate summary of mean value, SD, and overall and specific agreements calculations are provided in Appendix A. In terms of overall agreement of the experts, the results revealed that they have reached a consensus on all dimensions and indicators with an overall agreement of more than 60%, higher than the minimum acceptable consensus level of 50% (Zeeman et al., 2016; Esmaeilpoorarabi et al., 2018a). This finding indicated that dimensions and indicators are crucial for forming the classification framework of innovation districts and they were maintained for the Round 2 Delphi survey.

The highest overall agreement (highlighted in blue) was in the 80-94% range and the lowest agreement ranged from 60% to 78%. Similarly, SDs for expert's mean scores on all the 'dimensions' and 'indicators' are below the threshold of 2.42 points, which suggest that there is convergence and reliability in responses for the proposed dimensions and indicators. However, almost 54% (30 out of 56) of the recommended measures (highlighted in grey) had SDs above 2.42 points, indicating a weaker agreement amongst the experts. In terms of specific agreement (highlighted in light blue), 43% (24 out of 56) of the overall dimensions, indicators, and measures achieved consensus. The weak consensus among the experts could possibly be due to the lack of additional information on parameters and measures as pointed out by some of the experts in the comments section. The second-round survey, therefore, aimed to improve consensus for both the overall and the specific agreement for all the dimensions, indicators, and measures that are scored below the consensus level of 60% in Round 1. Generally, improvements in both agreement levels are expected to positively improve the relative SDs of experts' mean scores.

4.2.2. Round 2

A similar process applied in Round 1 for qualitative analysis was followed in Round 2. From the 32 experts invited, only 17 experts responded and re-assessed 1 dimension, 5 indicators and 43 measures, resulting a total of 49 responses. More than 90 comments were received through open-ended questions, focused again on experts' rationale for scores given and any further recommendations. Majority of the experts maintained their initial suggestion to use objective instead of subjective measures. There were additional suggestions for some renamed and new indicators, measures, and parameters, from which the researchers adopted the most relevant ones instead of conducting a Round 3 survey. Significantly, all the 'high-mid-low measures' (subjective measures) were changed to 'Excellent-Satisfactory-Unsatisfactory' or 'Significant- Exceptional-Insignificant' ones (objective measures). Indeed, the decision to not conduct a Round 3 survey was also supported and confirmed by Round 2 quantitative analysis results (as will be discussed below). Consequently, the classification framework, particularly the 'measures' category was further revised and finalised as illustrated in Table 4. A detail discussion on Table 4 can be found in the following section.

The discussion hereafter is focused on the changes between the two survey rounds in terms of the overall agreement, and the standard deviation of expert's mean scores. In terms of the percentage change in the number of 'agreements' for all attributes, the specific agreement increased by 9 percentage points, from 42.86% in Round 1 to 52.17% in Round 2, while the overall agreement increased by almost 14 percentage points, from 73.21% in Round 1 to 86.96% in Round 2. Overall, the percentage for 'specific agreement' highlighted in grey was slightly more than half (52%) of the total dimensions, indicators and measures. However, despite 87% of all the categories achieved an overall agreement, there is still inconsistency in experts' opinions as some categories such as 'Form', achieved an overall agreement but had a SD over the threshold of 2.42 points. Further analysis confirmed that such a case (as in 'form') will not negatively affect the finalisation of the classification framework as the calculated value of Cronbach's α for Round 2 was 0.956, indicating a good overall consistency in expert opinions. Concerning the SDs in expert's mean scores, the results revealed that the number of attributes with SDs higher than the threshold of 2.42 points reduced significantly by 27 percentage points, from 54% in Round 1 to 27% in Round 2. A considerably lower SD increased the overall level of consensus in Round 2 survey. Accordingly, the SD of experts' mean scores also decreased by 0.23 points, from 2.25 points in Round 1 to 2.02 points in Round 2 (see Appendix B for the calculations).

The tests for stability between the two survey rounds revealed that the Kendall's W was 0.785 for the mean and 0.919 for overall agreement, above the 0.5 cut off mark. Further, CV calculation changes between the two rounds was <15%. These results confirmed stability and consistency of experts' judgement. Consequently, as these results met the above-mentioned stop criteria for Delphi studies, the researchers decided to conclude the survey at the end of Round 2.

It should be noted that this study did not follow the 'rule of thumb' for Delphi studies where at the end of the final Delphi round, those attributes still below the consensus level are to be excluded from the final framework. Instead, the most affected ones, for example 'insignificant presence of social amenities' and 'unsatisfactory skilled employment' with the rest of lower or third tier measures were retained and included in the final framework. This is mainly because this study aimed to develop a classification framework that requires more than two-tier of measures, i.e. to use three-tier measures such as excellent (1st tier), satisfactory (2nd tier), and unsatisfactory (3rd tier).

4.3. The Framework

The significant outcome of the Delphi study is the multidimensional innovation district classification framework as displayed in Table 4, where the calculated mean scores reflect the levels of importance for individual dimensions, indicators and measures.

The developed framework comprised of 4 dimensions, 16 indicators and 48 measures. Although all these attributes were considered important for the classification of innovation districts, the 'Feature' dimension has the highest importance, followed by 'Context', 'Function' and 'Form'. Within the Feature dimension, 'social cultural setting' was the most important indicator, followed by both 'human capital and 'economic scale' as the second most important indicators, and 'locality setting' as the least important. The Feature dimension had a balanced mixture of both hard and soft indicators such as 'locality setting' (hard indicator) and 'human capital' (soft indicator), while other dimensions only consist of hard indicators as discussed below. Within the Context dimension, 'spatial system' was considered of higher importance than 'societal system', 'political system' and 'economic system'; Within the Function dimension, 'firm size classification' led the importance list followed by 'industry type', 'investment type' and 'management type' and within the Form dimension, 'green or blue infrastructure' led the importance list followed by 'land use', 'built environment' and 'space design'. It is noteworthy that in the final framework, the name of the fourth dimension was changed from 'space design & use' to 'form' following experts' recommendations.

Each indicator defined within four different dimensions has a three-tier objective measure, which is derived from the relevant multidisciplinary literature-based parameters. The use of objective measures is to avoid potential biases in the classification process of innovation districts. Most of the measures describe each indicator's conditions or significance relative to classifying innovation districts and provides parameters to distinguish between the thresholds for each of the three tiers. For instance, the measures for 'sociocultural setting' are: 'Significant', 'Exceptional' or 'Insignificant' presence of social amenities. The composite score weightings of the parameters are: >60 for Significant, >50 for Exceptional, and <50 for Insignificant (Taylor et al. 2011; Edwards et al., 2013). The other half of the measures use specific descriptions depending on the indicator type. For example, the measures for locality setting are: 'Inner city setting'; 'Suburban setting' and 'Regional setting' (Van Winden & Cavalho, 2016; Moonen & Clark, 2017; NSW-IPC, 2018).

Additionally, majority of the indicators employed different parameters for their measures, except for 'sociocultural setting'; 'societal system' and 'built environment' that employed composite score weightings. For instance, to measure the 'sociocultural settings' of innovation districts, relevant mapping tools such as google earth and google map will be utilised to identify the presence of social amenities. To measure 'human capital', a different parameter will be used. Demographic data from the Australian Bureau of Statistics, company profiles from the websites of various innovation district's and business directories such as Dunn & Bradstreet will be accessed to identify the number of knowledge workers with minimum bachelor's degree or higher, and the total number of workers employed within the innovation districts, respectively. The percentage of knowledge workers is calculated as total number of knowledge workers divided by total employment population of the innovation district.

In sum, the multidimensional classification framework is dominated by hard indicators, including locality setting, firm size classification, industry type, urban green or blue infrastructure and built environment, which play the leading role in the classification of innovation districts.

Table 6: The multidimensional innovation district classification framework

Dimension	Mean score	Indicator	Description	Mean score	Measure	Mean score
Feature	8.38	Social amenity	Presence or availability of social amenities for public use within the innovation district	8.81	Strong presence of social amenities	7.31
					Moderate presence of social amenities	6.56
					Weak presence of social amenities	6.00
		Human capital	Inventory of skilled people (i.e., information about the education and skill levels of the population and the potential stock of qualified people)	8.19	Strong human capital	8.06
					Moderate human capital	7.31
					Weak human capital	6.38
		Skilled labour	Skilled employment outcome of the innovation district activities	8.19	Strong skilled employment	8.00
					Moderate skilled employment	7.25
					Weak skilled employment	6.25
		Locality setting	Location of the district within the metropolitan area	8.13	Inner city setting	7.75
					Suburban setting	7.13
					Regional setting	6.13
Context	8.00	Spatial system	City-wide spatial layout and architecture qualities (e.g., physical environment, spatial conditions, physical urban development)	8.38	Strong spatial design	8.06
					Moderate spatial design	7.13
					Weak spatial design	5.63
		Societal system	Societal progress of the city (e.g., diversity, tolerance, equality, age structure, participation in cultural/community activities	8.19	Strong social assets	7.56
					Moderate social assets	6.56
					Weak social assets	4.94
		Governance system	Political progress of the city (e.g., political institution effectiveness, accountability, transparency, participation)	8.06	Strong governance effectiveness	8.44
					Moderate governance effectiveness	7.50
					Weak governance effectiveness	5.75
		Economic system	Macroeconomic progress of the city (e.g., monetary, and fiscal performance to maintain stability of economic growth)	7.50	Strong economic performance	8.06
					Moderate economic performance	7.13
					Weak economic performance	6.06
Function	7.81	Company size	Relative size of the firms within the innovation district (i.e., SME dominated, LNE dominated or MNE anchored)	8.06	Small and medium enterprise (SME) dominated	8.19
					Large national enterprise (LNE) dominated	8.13
					Multinational enterprise (MNE) anchored	8.06
		Industry type	Dominant business activity operating within the innovation district	7.63	Creativity intensive businesses	8.69
					Technology intensive business	8.56
					Business support services	8.44
		Investment type	Principal support and funding body for the development of the innovation districts	7.31	Public-private-community partnership-driven	8.69
					Public-private partnership-driven	8.25
					Public or private sector driven	7.10
		Property management	Management model of the innovation district's properties and activities	7.13	Building-based body corporate	7.50
					District-wide body corporate	7.13
					None	7.06
Form	6.38	Urban green-blue infrastructure	Aesthetic qualities of urban green and blue infrastructure within the innovation district (i.e., all natural and seminatural landscape elements that form a green-blue network)	8.06	Strong presence of ecosystem services	7.63
					Moderate presence of ecosystem services	6.75
					Weak presence of ecosystem services	5.69
		Land- use mix	Main land use types within the innovation district	7.94	Complex mix	8.44
					Mixed use	7.88
					Single use	7.13

	Built environment	Architectural design of built forms and functions encouraging open innovation systems, connectivity, and mobility within the innovation districts	7.94	Strong internal connectivity	7.50
				Moderate internal connectivity	6.50
				Weak internal connectivity	5.75
	Space design	Spatial layouts design encouraging open innovation system within the innovation district	7.69	Open layout plan	7.56
				Semi open layout plan	7.13
				Close layout plan	6.31

5. Discussion and Conclusion

Innovation districts are a new land use type that started to appear in cities as their development has become a highly popular urban policy. There is, however, limited information available to assist urban administrations to determine what type of innovation district is the right one for them. Particularly, there is a lack of holistic frameworks that can be used for classifying innovation districts, where such classification provides opportunity for identifying the most suitable type. This study focused on developing and validating such a framework as it is invaluable for urban administrators, policymakers and planners in understanding what works in certain locations and what does not, and informs their decisions in investing the type of innovation districts suitable for their local circumstances.

The multidimensional innovation district classification framework, the study developed, comprises four dimensions, ‘Context’, ‘Feature’, ‘Function’ and ‘Space use and design’, 16 indicators (four indicators for each dimension) and 48 measures (three measures for each indicator). The Delphi study findings confirmed that the framework is robust. ‘Feature’, ‘Function’ and ‘Space use and design’ are identified as primary classification dimensions, where ‘Context’ is seen as a secondary classification dimension as it generates city or regional level supporting information to be considered in decisions (Esmaeilpoorarabi et al., 2018a). The context indicators are kept in the framework as contextual or background information for the policymakers to consider.

Out of 16 indicators, two represent soft factors—i.e., ‘human capital’ and ‘skilled labour’ indicators of the Feature dimension—and the rest represent hard factors. Despite only a fraction of indicators covering the soft factors, they are listed among the top priority indicators. This finding not only suggests that the soft factors are equally important for the classification of innovation districts, but also shows that the inclusion of soft factors is an important obligation to be successful in the knowledge and innovation economy (Florida, 2005; Yigitcanlar et al., 2007; Alfken et al., 2015).

The high-priority hard factors are identified as ‘social amenity’ (Feature), ‘spatial system’(Context), ‘company size’ (Function) and ‘urban green-blue infrastructure’(Form) indicators. This indicates that the hard factors continue to play a leading role in the classification of innovation districts as they traditionally have been. For example, Forsyth’s (2014) classification framework has focused on hard factors of ‘location’, ‘physical scale of development’, ‘level of physical planning’ and ‘urban design’. Likewise, hard factors are critical for the knowledge and innovation economy. For instance, ‘social amenity’ indicator focuses on classifying innovation districts by determining the presence and availability of the social amenities for public use within the innovation districts. This indicator aligns with the knowledge and innovation economy’s socio-cultural development perspective (Yigitcanlar & Lönnqvist, 2013; Katz & Wagner, 2014). In other words, both the soft and hard indicators have critical roles in the classification of innovation districts and all the indicators comply with the requirements of the knowledge and innovation economy.

This study assembled a framework and thus provided invaluable insights for urban administrators and planners for the planning and development of innovation districts in their cities. Particularly, we envisaged innovation districts to be classified into typologies based on the indicator’s level of condition, significance and specific descriptions. However, developing typologies is beyond the scope of the study at hand. Nonetheless, our prospective studies will focus on developing generic typologies based on the presented framework through empirical studies of innovation districts in Australia and overseas.

Nevertheless, for the sake of giving an example, for instance, Typology A may compose of innovation districts that have all their indicators at the first-tier of measures with following characteristics: Strong social amenities, human capital and urban green-blue infrastructure; Strong skilled labour and built environments and located in the inner cities; Dominated by small and medium size enterprises in the line of creativity intensive businesses, and; Funded by multiple sectors and managed by a building-based body corporate. This type of innovation districts is designed for complex mixed-use developments and encourages open innovation system through their open layout plans. The other typologies may compose of innovation districts that have all their indicators at the second-tier of measures or a mixture of the first-, second- and third-tier of measures. Again, developing these innovation district typologies will form the core of our prospective research.

Lastly, it should be noted that this study did not follow the 'rule of thumb' for Delphi studies where at the end of the final Delphi round, those attributes still below the consensus level are to be excluded from the final framework. Instead, the most affected ones, for example 'weak presence of social amenities' and 'weak skilled employment' with the rest of lower- or third-tier measures were retained and included in the final framework. This is because the authors envisage that not all existing innovation district indicators will be rated on the first- and second-tier measures. There may be some whose indicators will fall in the lower-tier measure. Thus, it is necessary to include lower-tier measures in the classification framework to cater for such innovation districts. On this basis, this study developed a classification framework that has a three-tier measures—e.g., strong (first-tier), moderate (second-tier), and weak (third-tier).

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Appendix A: Round 1 Delphi survey results

Dimension	M	SD	A	SA	OA	Indicator	M	SD	A	SA	OA	Measures	M	SD	A	SA	OA
Context	8.28	1.89	12.51	78.13	90.64	Economic system	8.17	2.00	9.38	78.14	87.52	High-performance economic system	6.66	3.12	9.38	56.26	65.64
												Mid-performance economic system	5.90	2.77	9.68	38.71	48.39
												Low-performance economic system	5.17	3.28	9.68	32.26	41.94
						Political system	8.28	1.91	9.38	78.13	87.51	High-level governance effectiveness	7.00	3.26	12.51	62.51	75.02
												Mid-level governance effectiveness	6.38	2.98	9.68	51.61	61.29
												Low-level governance effectiveness	5.55	3.46	6.45	41.94	48.39
						Social system	8.10	1.90	12.50	75.01	87.51	High-level societal equality	6.69	3.32	6.26	62.50	68.76
												Mid-level societal equality	6.00	3.13	13.33	43.33	56.66
												Low-level societal equality	5.17	3.32	16.13	32.25	48.38
						Spatial system	8.00	1.60	18.76	71.88	90.64	High-quality spatial environment	7.00	3.04	15.63	59.38	75.01
												Mid-quality spatial environment	6.52	2.87	19.35	48.38	67.73
												Low-quality spatial environment	5.72	3.23	19.36	35.48	54.84
Function	8.17	1.34	21.88	71.88	93.76	Industry type	7.90	1.54	25.01	65.63	90.64	High-tech business intensive	8.28	1.79	15.63	71.89	87.52
												Creative business intensive	8.45	1.84	9.38	78.13	87.51
												Business support service intensive	8.00	1.81	15.63	68.76	84.39
						Investment type	7.62	1.57	37.50	53.13	90.63	Public-private partnership-driven	8.38	1.88	9.38	75.01	84.39
												Private sector-driven	7.69	1.83	9.38	68.76	78.14
												Public sector-driven	7.41	1.96	18.76	59.38	78.14
						Management type	7.55	1.55	37.50	53.13	90.63	District-wide body corporate	7.55	2.57	6.26	71.88	78.14
												Building-base body corporate	6.90	2.19	18.76	50.01	68.77
												No body corporate	6.69	2.58	15.63	50.00	65.63
Feature	8.10	1.82	25.00	65.63	90.63	Economic scale	8.31	1.63	12.51	78.13	90.64	High-level skilled employment	7.76	2.86	9.38	68.76	78.14
												Mid-level skilled employment	7.03	2.68	12.51	56.26	68.77
												Low-level skilled employment	6.07	3.21	9.38	43.76	53.14
						Locality setting	8.31	1.37	12.50	78.13	90.63	Urban (i.e., inner city)	8.03	2.38	12.51	75.00	87.51
												Suburban (i.e., suburban areas)	7.28	2.36	25.00	56.25	81.25
												Ex-urban (i.e., outside of suburban areas)	6.38	3.03	12.51	46.88	59.39
						Sociocultural setting	8.41	1.66	9.38	81.26	90.64	High-quality public/sociocultural places	7.55	2.57	9.38	62.50	71.88
												Mid-quality public/sociocultural places	6.59	2.82	9.38	50.01	59.39
												Low-quality public/sociocultural places	5.59	3.43	6.25	40.64	46.89
Space-use	7.76	1.86	18.76	65.63	84.39	Land use form	7.17	2.14	15.63	59.39	75.02	For work-learn-play-live uses	7.41	2.82	9.38	59.38	68.76
												For work-learn-play uses	7.03	2.69	3.13	59.38	62.51
												For work use only	5.97	2.98	9.38	37.51	46.89
						Built environment	7.59	1.90	21.88	62.51	84.39	High-level design qualities (e.g., open desig	6.90	3.19	6.26	56.26	62.52
												Mid-level design qualities (e.g., semi open d	6.00	2.73	15.63	40.63	56.26
												Low-level design qualities (e.g., close desig	4.97	3.01	9.38	25.01	34.39
						Natural environment	7.48	2.01	31.26	50.01	81.27	High-level presence of green/blue spaces	6.69	3.22	6.25	56.26	62.51
												Mid-level presence of green/blue spaces	6.24	3.17	18.76	40.63	59.39
												Low-level presence of green/blue spaces	5.10	3.45	12.51	31.26	43.77

Notes: M= Mean, SD= Standard devitaion, A=Agree (6 & 7), SA= Strongly Agree (8,9,10), OA= Overall Agreement (sum of A+SA)

=Overall Agreement >60%   =Specific Agreement>60% (separate calculations of A and SA)   = SD >2.42 (high dispersion level-lesser agreement)

Reliability Statistics

Cronbach's Alpha	Based on Standardized Items	N of Items
0.962	0.959	56

Case Processing Summary

		N	%
Cases	Valid	29	90.6
	Excluded[a]	3	9.4
	Total	32	100.0

a. Listwise deletion based on all variables in the procedure.

Consensus level cut off mark	**=60%**	
Agreement level summary:	**N=56**	**%**
Overall agreement	41	73.21
Specific agreement	24	42.86
Lesser agreement	30	53.57

Appendix B: Round 2 Delphi survey results

Dimension	M	SD	A	SA	OA	Indicator	M	SD	A	SA	OA	Measures	M	SD	A	SA	OA
Context	8.00	2.03	12.51	78.13	90.64	Economic system	7.50	2.34	9.38	78.14	87.52	Leading economic performance	8.06	2.14	23.54	64.70	88.24
												Moderate economic performance	7.13	2.09	47.06	35.30	82.36
												Low economic performance	6.06	2.91	35.30	23.53	58.83
						Political system	8.06	2.24	9.38	78.13	87.51	Leading governance effectiveness	8.44	1.67	29.41	64.71	94.12
												Moderate governance effectiveness	7.50	1.59	47.06	41.19	88.25
												Low governance effectiveness	5.75	2.82	29.42	23.53	52.95
						Social system	8.19	2.10	12.50	75.01	87.51	Leading social assets	7.56	3.05	17.65	58.83	76.48
												Moderate social assets	6.56	2.73	35.30	35.31	70.61
												Low social assets	4.94	3.23	17.65	23.53	41.18
						Spatial system	8.38	1.59	18.76	71.88	90.64	High quality spatial design	8.06	2.26	17.65	64.71	82.36
												Moderate quality spatial design	7.13	2.22	35.30	41.18	76.48
												Low quality spatial design	5.63	3.36	11.76	35.30	47.06
Function	7.81	1.42	21.88	71.88	93.76	Industry type	7.63	1.71	25.01	65.63	90.64	High-technology intensive businesses	8.56	1.90	11.77	76.48	88.25
												Creativity intensive businesses	8.69	1.58	11.77	82.35	94.12
												Business support services	8.44	1.21	29.41	70.59	100.00
						Investment type	7.31	1.82	37.50	53.13	90.63	Public-private partnership-driven	8.25	2.14	9.38	75.01	84.39
												Private sector-driven	7.31	2.06	9.38	68.76	78.14
												Public sector-driven	6.88	2.28	18.76	59.38	78.14
												Public-private-community partnership -driven	8.69	1.25	23.53	76.47	100.00
						Management type	7.13	1.67	37.50	53.13	90.63	District-wide body corporate	7.13	2.47	6.26	71.88	78.14
												Building-base body corporate	7.50	2.10	23.53	52.95	76.48
												No management	7.06	2.57	23.54	52.94	76.48
						Firm size classification	8.06	1.81	23.53	70.59	94.12	Multinational enterprise (MNE) anchored	8.06	1.45	23.53	70.59	94.12
												Small and medium enterprise (SME) dominated	8.19	1.56	23.53	70.59	94.12
Feature	8.38	1.41	25.00	65.63	90.63	Economic scale	8.19	1.22	12.51	78.13	90.64	High-level skilled employment	8.00	2.76	9.38	68.76	78.14
												Moderate level skilled employment	7.25	1.57	35.30	41.18	76.48
												Low-level skilled employment	6.25	3.21	9.38	43.76	53.14
						Human capital	8.19	1.22	23.53	76.47	100.00	High-level human capital	8.06	2.44	23.54	64.71	88.25
												Moderate-level human capital	7.31	2.13	35.30	52.94	88.24
												Low-level human capital	6.38	2.28	29.42	35.29	64.71
						Locality setting	8.13	1.67	12.50	78.13	90.63	Urban setting	7.75	1.88	29.41	52.94	82.35
												Suburban setting	7.13	1.45	35.30	41.19	76.49
												Ex-urban setting	6.13	2.45	29.42	29.41	58.83
						Sociocultural setting	8.81	1.28	9.38	81.26	90.64	High presence of social amenities	7.31	2.24	23.54	52.94	76.48
												Moderate presence of social amenities	6.56	2.09	41.18	29.42	70.60
												Low presence of social amenities	6.00	2.63	29.42	29.41	58.83
Form	6.38	3.22	23.53	47.07	70.60	Space design	7.69	2.68	29.41	58.83	88.24	Open layout design	7.56	2.16	23.53	58.83	82.36
												Part open layout design	7.13	2.22	11.77	58.82	70.59
												Close layout design	6.31	2.85	5.88	47.06	52.94
						Land use	7.94	2.08	23.53	64.70	88.23	Work only	7.13	1.86	47.06	35.31	82.37
												Work-learn-play	7.88	1.93	17.65	70.59	88.24
												Work-learn-live	7.88	2.09	17.65	64.71	82.36
												Work-learn-play-live	8.44	2.19	11.77	76.47	88.24
						Built environment	7.94	1.77	21.88	62.51	84.39	High-level design qualities (i.e., built form, function, and connectivity)	7.50	2.31	17.65	64.71	82.36
												Mid-level design qualities (i.e., built form, function, and connectivity)	6.50	2.07	35.30	35.29	70.59
												Low-level design qualities (i.e., built form, function, and connectivity)	5.75	2.82	41.17	29.42	70.59
						Urban green-blue-infrastructure	8.06	1.95	23.54	70.59	94.13	High-level presence of green or blue infrastructure	7.63	2.63	17.65	64.71	82.36
												Mid-level presence of green or blue infrastructure	6.75	2.41	35.30	41.18	76.48
												Low-level presence of green or blue infrastructure	5.69	3.09	17.65	35.30	52.95

Notes: M= Mean, SD= Standard devitaion, A=Agree (scores 6 & 7), SA= Strongly Agree (scores 8,9,10), OA= Overall Agreement (sum A + SA)

= overall agreement >60% = specific agreement >60% (separate calculations of A and SA) = SD >2.42 (high dispersion level-lesser agreement)

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
0.956	0.963	69

Case Processing Summary

		N	%
Cases	Valid	16	94.1
	Excluded[a]	1	5.9
	Total	17	100.0

a. Listwise deletion based on all variables in the procedure.

Consensus level cut off mark	**= 60%**	
Agreement level summary:	**N=69**	**%**
Overall agreement	60	86.96
Specific agreement	36	52.17
Lesser agreement	19	27.54

Test Statistics - ∑Mean (R1-R2)

N	2
Kendall's W[a]	**0.785**
Chi-Square	106.818
df	68
Asymp. Sig.	0.002

a. Kendall's Coefficient of Concordance

Test Statistics- ∑Overall Agreement (R1-R2)

N	2
Kendall's W[a]	**0.919**
Chi-Square	125.018
df	68
Asymp. Sig.	0.000

a. Kendall's Coefficient of Concordance