谢友柏设计科学研究基金项目
年度报告

项目名称：互联网群智协同创新环境下有效用户知识贡献行为演化及其驱动模式研究

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1. 年度计划研究内容

2021.1—2021.6　基于典型创新项目构建有效参与者交互网络，形成用户能力度量指标体系，构建参与主体角色及行为演化细分模型。

2021.7—2021.12　分析各类创新角色能力外化形式，构建面向不同角色的识别指标体系，研究对应的指标量化方法，开展对比实验。

2. 年度研究进展及成果

2.1 年度研究进展

根据研究计划，本年度主要围绕众包工业设计模式、参与主体分类及特征、群智设计生态网络系统等展开了研究。

2.1.1 众包工业设计模式

2.1.1.1 众包工业设计模式总体架构

众包工业设计旨在激活自由设计师、产品资深用户、跨领域工程师、高校师生等企业外部闲散资源，利用其所掌握的专业技能、跨域知识、体验、需求、创意、经验等协助企业开展设计创新活动。相较传统模式，众包设计由于项目开放性、人员流动性强，在实施过程中更容易出现设计资源不稳定、知识产权归属不明确等问题，因此众包工业设计模式构建需要综合考虑设计需求与能力匹配、设计标准与规范性、设计项目过程管控等方面的要求。

围绕资源、规范、管控构建如图 1 所示的众包设计模式总体框架。该框架主要包括用户层、平台层、规范层、应用层 4 个层级。分别描述了众包设计模式在资源聚合、平台工具、规范协议、实践应用等方面的内容要素。

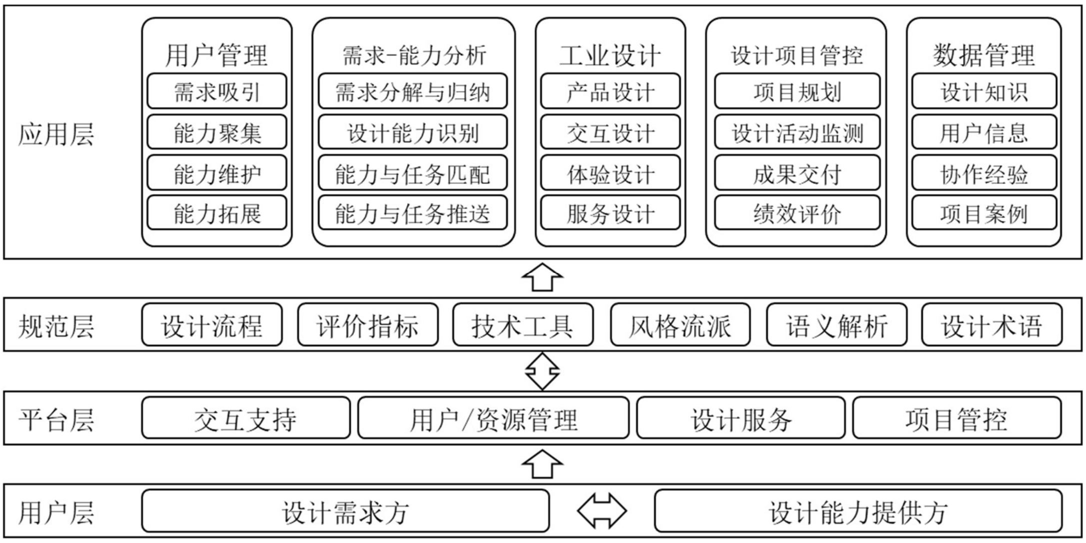


图 1　众包工业设计模式总体框架

2.1.1.2 众包工业设计用户层

用户层包括众包工业设计最关键的参与主体：设计需求方与设计能力提供方。两类主体既是众包模式得以实施的基础资源，也是该模式的服务对象，前者寻求设计解决方案，后者通过提供能力获取收益。无论是需求方还是能力方，人员构成复杂，专业领域多样，因而需要具有针对性的招募、组织、激励措施以保证用户资源池的有效构建与稳定运维。

（1）设计需求方 工业设计所涵盖的领域十分广泛，从产品造型设计到包装设计，到平面设计，甚至到珠宝、首饰设计，因而设计需求方的社会身份往往也多种多样。根据是否具有设计开发经验，需求方可被划分为设计相关行业与其他行业，前者可包括制造型企业、科研院所、文化创意机构等，后者可包括政府机关、服务机构、卫生系统等。设计相关行业熟悉领域规范与标准，所提出的需求多为结构化、易识别的内容；其他行业对设计规范、准则等相对陌生，提出的需求往往为非结构化内容，需要经过扩充与处理后才能转化为设计指导信息。

（2）设计能力提供方 相较需求方，能力方的成员结构更为复杂：除了具备设计能力的相关个体或组织如设计师、工程师、设计公司、技术团队外，还包括

相当一部分不具备设计从业能力的人员如产品资深用户、品牌粉丝、跨领域学者等。前者可以为需求方提供设计创新、技术开发、功能规划等方面的专业服务，后者则能够提供设计创意、使用体验、用户诉求、跨学科知识等资源。不同层次的能力提供者在众包设计参与方式、行为特征等方面也会存在一定差异，如专业设计人员大多富有契约精神、纪律性较强，无需借助在线工具即可形成完整方案；其他人员则有可能需要依托辅助工具或在相关人员协助下才能完成创意、观念的表达。表 1 归纳了较为常见的设计能力方类型及特点。

表 1　常见设计能力方类型及特征

能力方类型	职业状态	人员类别	参与项目时段	可承担任务类型	设计支持需求
专业人员	全职工作	设计师、工程师、产品经理、技术开发人员、相关专业教学人员/学者/科研人员等	夜间、节假日等业余时间	设计与技术咨询、市场与用户研究、创意与简单设计方案生成、原型测试等（适合参加低强度、短期设计项目）	不需要或仅需较少辅助
	非全职工作	自由设计师、独立工程师、大专院校相关专业学生等（设计公司/事务所/工作室、技术公司/开发小组等组织可以自由承接各类设计委托，故也归为非全职工作）	全天候	创新设计、技术开发、咨询、市场与用户研究、创意生成、原型测试、迭代升级等（可以承担大多数设计任务，且能与需求方保持长期合作）	不需要或仅需较少辅助
非专业人员	/	产品/服务资深用户、品牌粉丝、关联行业从业人员、跨领域学者等	夜间、节假日等业余时间	跨领域知识与实践咨询、市场与用户研究、创意生成、原型测试等	需要提供辅助工具帮助非专业人员实现对创意、设计方案等的表达

2.1.1.3 众包工业设计平台层

众包工业设计平台层依据众包设计模式在资源稳定性、需求与能力匹配、项目过程管控等方面的需求，构建用户/资源管理、交互支持、设计服务、项目管控 4 个子系统，具体平台架构如图 2 所示。

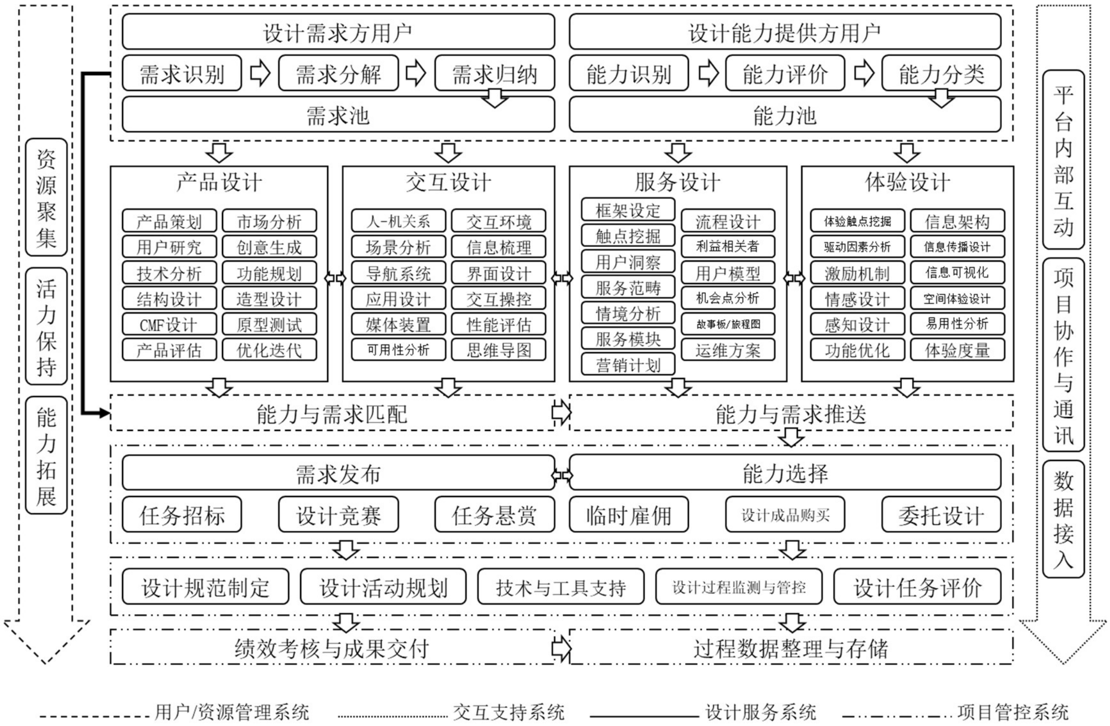


图 2　众包工业设计平台层架构

（1）用户/资源管理系统 该系统的主要功能是实现用户招募、分类、保持以及需求与能力识别、匹配、推送等，包括需求资源、能力资源、匹配推送、管理维护 4 个功能模块。其中需求资源模块在专家系统与基于机器学习的智能识别与分析工具支持下实现对需求的识别、拆解及归纳分类，进而形成包含细分化需求的资源池；能力资源模块在用户自述、考核评价、智能分类等工具支持下实现对能力的识别、认证与分类，并构建能力资源池；匹配推送模块基于关联与映射规则、求解模型、配对算法以及人工修正实现需求与能力的匹配，进而通过内容推送工具分别为需求方与能力方提供合适的能力资源与需求任务信息。

（2）交互支持系统 交互系统主要实现站内交流与通讯、项目协作、数据资

料共享等功能，包括平台内部互动、项目协作通讯、数据接入 3 个功能模块。其中平台内部互动模块包括论坛、博客、站内信等工具，可以支持用户开展线上社交活动、需求与能力展示、需求方与能力方合作前研讨等；项目协作通讯模块包括即时通讯、虚拟会议、在线设计工具（如图像处理、三维建模、渲染）等，支持众包项目各参与方进行项目研讨、设计协作、方案展评等；数据接入模块包括综合接口、数据库、权限管理等工具，支持设计相关数据的上传与调用。

(3) 工业设计服务系统 该系统与用户/资源管理系统中的能力池密切相关，能力资源入驻平台后，根据其能力特征、领域、水平等与产品设计、交互设计、服务设计、体验设计 4 类服务模块进行关联。其中产品设计模块主要提供用户研究、产品策划、造型设计、功能规划、结构设计等方面的服务；交互设计模块提供人机环关系规划、场景分析、操作界面设计等服务；服务设计模块提供服务触点挖掘、利益相关者分析、运维方案构建等服务；体验设计模块提供情感设计、功能优化、易用性分析等服务。4 类服务模块相互支撑、相互补充，构成健全完整的工业设计服务体系。

(4) 项目管控系统 该系统的主要功能是协助需求方选择合适的需求发布方式及设计能力，管理项目进程，监督成果交付与报酬支付，采集、分析项目全局数据。包括需求发布与能力选择、项目管控、项目后处理 3 个功能模块，其中需求发布与能力选择模块根据需求类型、复杂度、专业领域等为需求方推荐适宜的需求发布与委托方式如招标、竞赛、悬赏、临时雇佣、计件等，根据用户/资源管理系统的匹配结果，向需求方推荐合适的设计能力提供方；项目管控模块协助需求方组织实施众包设计项目（包括规范制定、流程规划等），为能力方提供设计支持工具、软件等，监控项目各参与方状态、诊断并处置项目过程中出现的问题，

协助需求方完成对设计成果的评价等; 项目后处理模块负责考核能力方的工作绩效，为成果交付和薪酬支付提供担保，收集并分析项目全局数据，为众包设计模式优化改进提供资料信息与实证反馈。

2.1.1.4 众包工业设计规范层

众包工业设计规范层旨在通过确定设计协同过程中的执行标准/规范、成果交付/绩效考核方式、知识产权归属来保证设计项目高效有序的实施，实现设计过程的标准化、有序化。根据众包设计在标准与规范性方面的需求，建立规范层构架。

（1）设计执行标准/规范 工业设计实施过程中需要遵循众多规范、标准等，如“标准色规范”、“交互操控容错原则”等，然而，目前大多数企业所执行的设计标准都属于企业自定内容，如潘通公司（Pantone Inc.）的标准色卡等，国家、地区、行业标准较为匮乏。另外，工业设计领域流派众多、风格各异，如强调理性分析，弱化个人风格的理性主义设计；突出大众化、通俗化趣味，追求新颖、稀奇的波普风格等，不同设计师、企业在设计风格方面往往存在一定的倾向性，且特定用户群体、细分市场对于某些风格流派也会有一定的偏好。再次，拥有不同教育背景、从业经历的设计师在表述方式、习惯用语、设计工具/软件、设计流程步骤等方面也会存在一定的差异。因此，需要通过规范层将需求方与能力方的标准规范体系协调统一，以保证设计项目的有序开展。

（2）成果交付/绩效考核方式 相较传统的组织内部创新，基于在线平台的众包模式在对设计能力方的工作行为及取得的工作业绩/成果的管理与评估方面存在一定的不足，项目管理者难以实时了解分布各地的参与者的履职情况，且在报酬支付后很难获得能力方的进一步支持。因此，需要在项目初始阶段即针对成

果、绩效等形成统一管理规范，其中，围绕成果交付，根据众包项目组织形式、产品特点、需求结构等设定适宜的交付方式（如阶段性交付、项目完结统一交付等），另外，由平台方提供担保，设置一定的优化改进期，以保证设计的质量和效果；在绩效考核方面，根据项目规模、研发周期等对阶段性目标、设计评审方法、考核方式、协作机制、激励措施等进行设定，同时，项目酬金由平台方代为管理，以保证能力方的权益。

（3）知识产权归属 众包工业设计本质上是一种多主体协同创作过程，不同参与者可对同一作品/方案进行优化、改进、再创作等，因而，在产权方面容易出现矛盾和纠纷。鉴于此，在众包设计项目开展前即需要明确设计成果的知识产权归属。由劳伦斯·莱斯格发起的知识共享组织（Creative Commons, CC）围绕公共著作权构建了一种许可协议体系可用来处理不同性质众包设计项目的权力归属，该体系对设计成果的署名权、共享权、使用权、演绎权、收益权等进行了规定，并通过对协作案例的学习不断扩展协议的适用范围。

2.1.1.5 众包工业设计应用层

（1）用户管理

针对众包工业设计参与者的管理主要从平台与项目两个层级展开，其中，对于前者，平台管理方需要在网站建设、运营过程中不断招募来自工业设计各领域的能力贡献者，并通过一定的激励策略保持其参与活力；同时，管理方还要尽可能多的吸引需求方入驻平台，适时扩大需求规模，并根据需求方的委托内容动态扩增设计能力，从而形成“平台主动吸引+需求牵引扩充”的能力生长机制。对于项目层级，平台管理方与需求方基于规范层所形成的项目实施办法对参与设计的个体进行组织与引导，同时，根据项目需求适时吸纳新的设计能力并裁汰无效参

与者。实践过程中需要重点解决用户吸引、活力保持、能力转化等问题。

（2）需求-能力分析

需求方委托的设计任务经过平台分析处理后进入需求池，设计能力则在通过平台考核/认证后进入能力池。平台从专业归属、设计范畴、技术层次、能力水平等方面对需求池与能力池中的资源进行关联分析，实现需求与能力的匹配。通过站内信系统将需求推送给适合的设计能力方，并在能力方搜索设计任务时将与其匹配度较高的需求针对性置顶；同时，为需求方提供具备任务承担资格的设计能力方推荐名单，实现需求方与能力方的双向选择与精准对接。需求与能力的精准匹配是实践过程中需要重点解决的问题。

（3）工业设计

平台设置工业设计服务模块，并根据能力池当中设计参与者的专业及技术方向，将其分配至产品、交互、体验、服务 4 个子模块，由于工业设计各领域相互重叠，因此能力方往往同时服务于不同子模块。需求池中的任务资源经由平台处理后自动匹配至对应服务子模块，需求方可在模块中招募具备相应能力的个体来协助其解决设计问题；同时，工业设计服务模块也要根据需求内容适时扩增服务类型。面向 4 类子模块的能力均衡配置是实践过程中需要着重解决的问题。

（4）设计项目管控

设计项目正式开展前，平台管理方与需求方在对项目规模、设计难度、产品特征等系统分析的基础上明确实施方式、管理规则、执行标准、绩效考核、成果交付等内容，构建完善、有效的规范层。在项目实施过程中，平台协助需求方收集能力方行为数据、判断参与者状态，汰换无效、低效设计人员，激励有效参与者，并适时扩充设计队伍。在项目里程碑节点，平台辅助需求方完成对能力方的

考核、对设计方案的评价，并保证需求方及时、足量的支付设计薪酬。实践过程中需要重点关注参与者行为分析、状态判断、能力考核等方面的内容。

（5）数据管理

由于设计需求的不同，各类众包设计项目在流程特征、实施细节等方面也会呈现出一定的差异性；另外，不同个体/组织在设计项目参与过程中所表现出的行为特点也有所差异，这些差异使得众包模式必须不断改进、迭代以保证设计有效性。因此，设计服务平台需要全程收集各个项目的过程数据，并通过不间断学习、分析数据实现对模式的动态优化。

2.1.2 参与主体分类及特征

随着零工经济与众包模式的不断演进，群智协同设计的组织形式也获得了新的发展，逐渐呈现出“平台组织引导-用户循规参与”的特点：以用户群作为创新主体，平台协助企业制定研发流程、分配资源，用户在平台引导下有计划的提出创新想法与技术方案，并共享各类信息与设计结果。其核心思想在于平台与企业掌控创新进程，根据项目需求聚集广泛的群体智能作为创新源，通过“引导-协作”的方式解决设计难题，提高创新效率及资源利用率。

生态系统，是指在一个特定环境内，相互作用的所有生物和该环境的统称。此特定环境中的非生物因子（如空气、水及土壤等）与所包含的生物之间不断交互，时时进行物质的交换和能量的传递，并借由物质流和能量流的连接，而形成一个整体。产品群智设计的系统组成与生态系统有一定的相似性，也可以认为是以产品设计与生产为活动中心的人工生态系统。产品群智设计生态系统依托互联网平台，以相关利益方为主体，以知识服务交易为核心，以用户需求、资源管理、知识网络、过程优化、金融体系、专业团体为要素，通过一定的交易规则向产品

或服务的供需双方提供设计服务，促成交易并获取收益，是一个长期处于竞合共生、开放动态的具有跨边网络效应的复杂系统。设计生态系统具有整体性、复杂多样性、层级性、混沌边缘趋向性、目的明确性、可持续发展性等特征。

在产品群智设计生态系统中，主要包含三类活动主体：需求主体、设计（资源）主体与平台主体。有设计需求或关键技术问题的需求主体，可以是政府组织、企业、机构或个人，往往存在自身难以解决或无法解决（亦或是自行解决成本较高）的瓶颈问题，以提供一定的经济报酬为条件，通过众包社区或平台来寻求更多的外部帮助，这类群体类似于生态系统中的生产者，他们是食物链的最底端。设计主体是指主动参与平台中发布的设计活动的个人或组织，他们出于经济利益、提升自身设计创新实力、兴趣等方面的原因，自发参与平台的任务活动。根据需求主体所发布设计任务的要求，设计主体之间会存在不同程度的合作或竞争关系，设计主体是生态系统中的捕食者，他们以问题或需求提供者的经济报酬为“食”，当能够独立解决问题时，设计主体间呈现竞争关系，当问题获设计需求难度较大、不易独立解决时，设计主体会呈现合作关系。平台主体是发起众包社区或平台的政府机关、企业或机构等，基于不同的目标如提供开放资源、辅助决策、关键技术攻关等，建立一个以设计服务、知识共享为核心的开放式的众包平台，吸引并汇集需求主体和设计主体共同参与，类似于生态系统中的非生物环境，为“生产者”和“捕食者”提供赖以生存的物质环境。三类主体内部、主体间存在多种关系，主要包括：种内关系——种内互助与斗争，种间关系——种间互助、竞争、共生、捕食等。

2.1.3 群智设计生态网络系统

本项目与国家重点研发计划项目“支持个性化设计的众包平台研发”建立了

稳定的合作关系，依托天津大学、重庆大学、西南交通大学、三峡大学、江南大学等院校联合开发的众包生态网络系统工具，对群智设计生态网络系统的主体间关系进行了初步分析。

2.1.3.1 群智设计生态网络关系

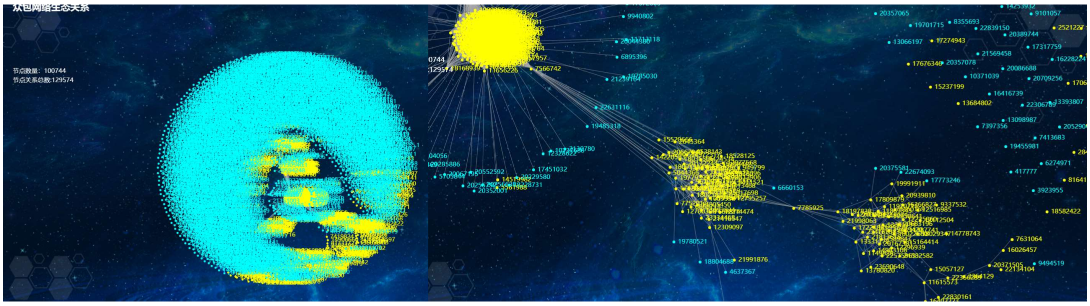


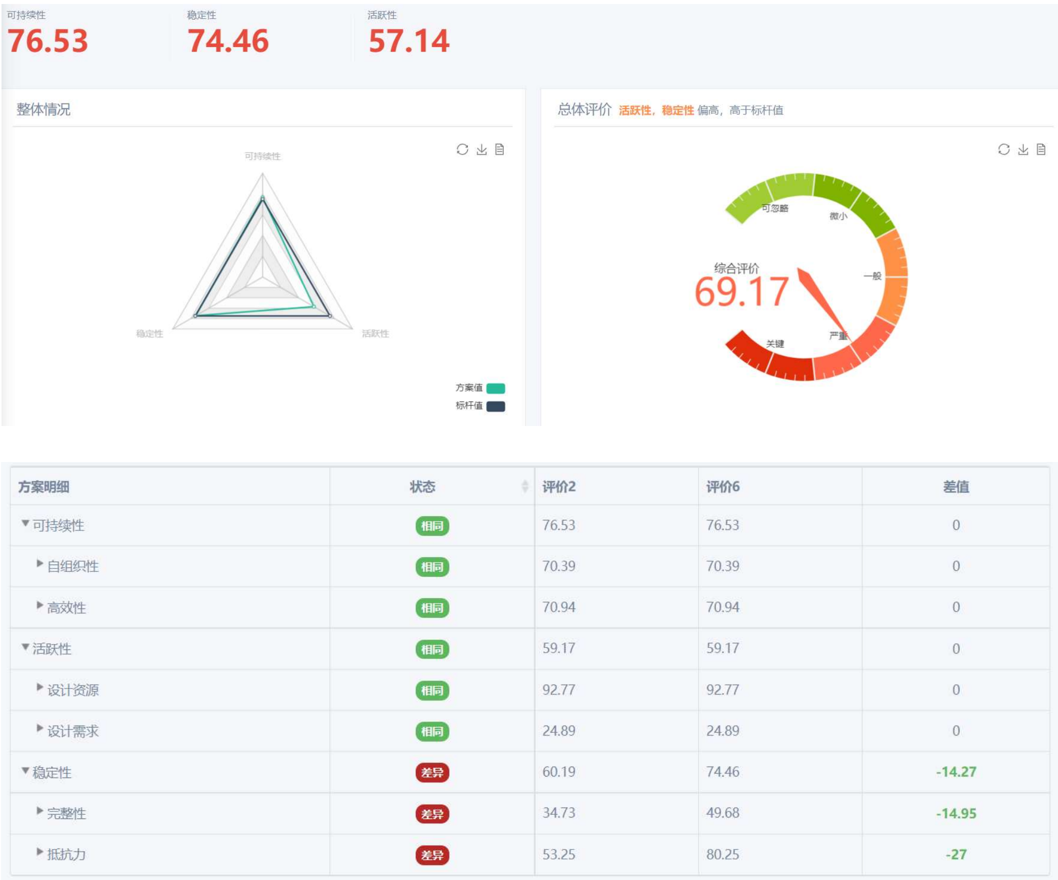
图 3 群智设计生态网络系统可视化模型

利用爬虫工具对某互联网众包创新平台的已公开项目数据进行抓取，统计单位时间内出现在平台上的需求主体、设计主体总量及需求数量、方案数量、交易情况等。利用社会网络分析工具建立需求与设计主体、设计与设计主体之间的交互关系，在此基础上，通过生态网络构建工具，形成反映群智设计生态系统特征的可视化网络模型，如图 3 所示，该模型能够直观反映设计活动参与节点与项目、其他节点之间的互动关系以及方案采纳、项目交易情况。

2.1.3.2 群智设计生态网络系统效能评价

通过综合分析群智设计生态网络系统的活跃性、稳定性及可持续性实现对生态网络自我维持与抗干扰能力的评价。对众包设计生态系统活跃性的评价主要从设计需求、设计资源、设计服务三个方面展开，综合考虑订单、活跃度、参与度、价值结构、设计效率等指标因素。对稳定性的评价主要从保持率、完整性、抵抗力三个方面展开，综合考虑各方保持率、功能多样性、服务质量、抗干扰性等指标因素。对可持续性的评价主要从高效性、协调性、自组织性三个方面展开，综合考虑各方利用有效性、收入基尼系数、流失系数等指标因素。通过爬虫工具获

取众包创新平台项目数据，使用效能评价工具从上述三个方面对设计生态网络系统进行评价，结果如图 4 所示。评价工具包含多套评价方案，适用于不同类型、组织模式的创新项目；通过对大量典型成功案例及平台运维数据的系统分析，形成了可持续性、稳定性与活跃性标杆值，当生态系统三类指标值与标杆值相近时，则说明生态系统健康度较高，反之，则说明生态系统存在待优化的部分。



方案明细	状态	评价2	评价6	差值
▾可持续性	相同	76.53	76.53	0
▸自组织性	相同	70.39	70.39	0
▸高效性	相同	70.94	70.94	0
▾活跃性	相同	59.17	59.17	0
▸设计资源	相同	92.77	92.77	0
▸设计需求	相同	24.89	24.89	0
▾稳定性	差异	60.19	74.46	-14.27
▸完整性	差异	34.73	49.68	-14.95
▸抵抗力	差异	53.25	80.25	-27

图 4　群智设计生态网络系统效能评价

2.2 年度成果

本年度形成的主要成果包括论文两篇，其中论文一（题目：How to Find the Key Participants in Crowdsourcing Design? Identifying Lead Users in the Online Context Using User-Contributed Content and Online Behavior Analysis）发表于 SSCI 期刊 Sustainability；论文二（题目：Why do they quit? Investigation of crowdsourcing innovation discontinue participation intentions: a computer self-efficacy perspective）已经撰写完成，目前处于审稿过程中。附件为论文一刊出稿，由于论文二尚未正式发表，故本次报告未附上。

（成果可以是未发表的研究报告、论文稿、专利稿，成果发表均需标注有“谢友柏设计科学研究基金资助”字样）

附：上述研究成果全文或实体，成果不能在互联网上传递的可以邮寄到学委会秘书组。

sustainability

Article

How to Find the Key Participants in Crowdsourcing Design? Identifying Lead Users in the Online Context Using User-Contributed Content and Online Behavior Analysis

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Abstract: Lead users are the most valuable innovation sources in crowdsourcing design; how to identify these users is a research hotspot in the field of design and management. Existing approaches to discover lead users in the context of the online community, such as the manual method and ordering algorithm, have some limitations, for instance, low coverage and accuracy. To address these deficiencies, this article proposes a method that applies text-mining techniques, analysis of user behavior, and contributed content to identify lead users. We suggest a three-step analytical approach: First, a criterion system to evaluate the user's leading-edge status is constructed. Second, we utilize a fuzzy analytical hierarchy process to assess the weighted value of each indicator and develop the reference sequence of the indicators. Third, grey relational analysis is employed to analyze the correlations between users' indicators and reference sequences, and lead users are recognized based on each user's correlation ranking. An empirical analysis is used to examine the effectiveness of the proposed method. The results reveal that the method has good precision and recall rate, can automatically process large-scale data, and has no strict requirements for respondents. Finally, the article discusses the limitations and provides possible directions for future research.

Keywords: crowdsourcing design community; lead users; innovation; lead user identification; user behavior; user-contribution content

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1. Introduction

In recent years, the flourishing of crowdsourcing triggered a transformation in the field of product development [1]. More and more companies have realized that customers are crucial external innovation sources and are expected to establish long-term relationships; some enterprises have started collaborating with customers to design/develop new products or services [2]. The advancement of Internet technologies has offered a stable channel for consumers to participate in design activities. Many firms, such as Lego, P&G, Haier, and Dell, have launched online platforms, i.e., the crowdsourcing design community (CDC). It encourages customers to contribute content (e.g., designs and ideas) via posting topics and messages, which is the main pathway for users to participate in enterprises' new product development (NPD) projects [3,4]. For instance, Dell initiated a crowdsourcing platform called Ideastorm for NPD. Dell posts its needs (e.g., bottleneck problems the company encounter during the process of NPD) on Ideastorm and invites users to contribute ideas, designs, experience, and knowledge to solve these issues. With the Ideastorm strategy, Dell's NPD productivity has increased by almost 50 percent; many of Dell's best-selling products are coming from Ideastorm [5]. The CDC extends the communication channel between companies and customers, providing a new approach for enterprises to continuously acquire new ideas and external knowledge [6]. Moreover, as a critical innovation force, users can exert significant effects on the success of NPD.

In the research field of sustainable crowdsourcing design, scholars have acknowledged that companies should employ users with rich experience, extensive knowledge, and great skill concerning technologies and usage of various types of products as long-time partners to develop new products [7]. With these individuals' assistance, enterprises can effectively decrease the research and development (R and D) costs, shorten development cycles, increase the probability of project success, and improve design efficiency [8]. Eric von Hippel defined these individuals as lead users and considered customers of a product/service. The current experience needs will be general in a marketplace in the future and benefit gratefully if they obtain a solution to these needs [9]. These individuals may speed up product R and D and promote the sustainable development of enterprises. Lead users have two typical features: first, their needs represent the development trends of the product/service; second, they are keen to participate in design projects to translate their needs into new products/services [10]. Since lead users are the most valuable participants in sustainable crowdsourcing design activities, how to identify these individuals with high efficiency is an important research issue in the area of open innovation and information systems.

The CDC is the primary medium for enterprises to organize crowdsourcing design events. The operators may launch product development projects and design challenges within the community. Users can participate in their preferred activities and contribute content via posting feedback and messages to solve design-related issues. Additionally, the enterprise encourages users to interact with others in the community; many members often initiate topic discussions on technology, product improvement, usage experience, requirements, et al. and reply to other users' posts. Members' contributed content can fully reflect their capabilities, expertise, and active degree, which may assist the company managers in discovering critical users (e.g., lead users and opinion leaders) [11].

Research on the discovery of lead users in social media (e.g., social network sites and online communities) is still at the initial stages. In particular, strategies to identify these users in the context of online communities have not been sufficiently explored [12,13]. The existing literature primarily introduced two kinds of methods to discover lead users: manual screening and an ordering algorithm based on influence rank [11]. The main goal of the former method is to let the community members recommend lead users. It has multiple tools, such as surveying, interviewing, and discussing. Although the manual screening method has been extensively applied in the research area of product development, it has some limitations, such as low coverage, high cost, and intense subjectivity [9]. The latter method aims to identify the lead users by evaluating the frequency of content contributed by community members and their social influence. Such a method can be utilized to handle large samples sizes. However, their accuracy is relatively low. Most of the users identified by the ordering algorithm are opinion leaders who may have a poor understanding of technologies and usage of products [13]. To accurately and efficiently recognize the lead users in the context of the CDC, this work proposes an integrated method combined with user-contributed content and online behavior (mainly contribution behavior) analysis. The content analysis is performed using text-mining technology, while the behavior analysis is implemented adopting the statistical tool of online user behavior. The main contributions of this study are as follows:

(1) We propose integrated criteria that measure individuals' expertise and active degree.
(2) Text-mining techniques are applied to extract product-related, innovation-related, user demand-related, et al. information from user-contributed content in CDC.
(3) A ranking system based on fuzzy analytic hierarchy process (FAHP) and grey relational analysis (GRA) is developed to identify lead users.
(4) We demonstrate the efficacy of our proposed methodology utilizing a case study of user behavior data from a well-known CDC in China.

To sum up, the critical contribution of this study is to propose an innovative lead user identification method. On the one hand, this method can help the traditional manual method quickly screen target users in the ordinary network environment (such as microblog, Facebook, and Twitter). On the other hand, it can quickly and automatically identify lead users in the specific network environment of a crowdsourcing innovation platform.

The remainder of this article is organized as follows. Section 2 reviews the relevant literature on lead user identification. In addition, Section 3 describes our proposed method in detail. Next, Section 4 presents the case study. Section 5 discusses the experimental results. Finally, Section 6 draws the conclusions.

2. Related Works

2.1. Crowdsourcing Design in the Context of Online Platforms

Companies that desire to perform sustainable crowdsourcing design should continuously motivate users to contribute knowledge, ideas, designs, and innovations. An approach for enterprises to collect these resources is to run a CDC. Such a community often starts as a consumer support platform (e.g., brand community). Customers exchange information (e.g., usage attentions and tips) of the company's products and evolve into a way by which users can put forward suggestions on product improvement and develop extensions [14,15]. Companies may adopt some of the good ideas contributed by the customers and develop the products according to their needs [16]. Besides, enterprises often post the issues they meet in NPD and encourage users to contribute content to solve these problems. Sometimes users may provide unconventional but effective solutions. Although CDC has been widely used for implementing open innovation, previous studies have paid little attention to systematically exploring users' features and participation behavior in such a context. Therefore, more in-depth research is necessary.

Another method for firms to initiate sustainable crowdsourcing design is launching a design contest website [17,18]. Enterprises put their needs (for technology, products, e-commerce, et al.) on specific sections within the platform. Members can find the need that matches their innovation capability through the retrieval system [19]. The operators will choose the best designs/ideas as solutions for the needs and pay the members for their contributions [20]. Members will try their best to beat the opponents to get the reward. OpenIDEO hosted by IDEO, HOPE hosted by Haier, and Cuusoo hosted by LEGO are typical design contest website representatives [21].

2.2. Manual Method to Discover Lead User

Research on the lead user in product design and innovation is mainly focused on identifying consumers who contribute innovative ideas that are ahead of market preferences and trends [11,22]. In the offline context, manual screening of a significant number of potentially relevant customers is the primary method to evaluate and identify lead users [23]. Hippel et al. first probed the identification methodology and proposed a screening and pyramiding method to search lead users [9,24]. A representative sample or a predefined population is screened for users who satisfy a particular criterion via questionnaires to perform screening [9,13]. The examined sample should be sufficiently large to discover the real lead users. Pyramiding is the improvement of screening; it is a more targeted method that dramatically reduces screening efforts. To implement pyramiding, researchers must build the pyramid of expertise that contains three layers: the lead users, the users who have good knowledge of the product and can find the lead users, and the users who have an understanding of the product domain and may find the advanced experts [24]. The researchers may contact any users of these layers and follow the chain of user recommendations to find the next-level users. This method is effective since respondents with vital interests in specific topics tend to know the senior experts in the area [12].

Many scholars have further developed Hippel's strategy: Lüthje [25] empirically explored the features of innovation participants and considered that researchers should incorporate more indicators such as user influence, innovation ability, and forward-looking expectations to perform screening. Morrison et al. [26] applied leading-edge status to measure the users' level of expertise. Their research results revealed that applications' innovativeness is one of the most critical features of lead users. Tietz et al. [27] proposed a signaling method that utilized advertising tools to discover lead users; such an approach can broadcast the survey information to attract more target users. Brem and Bilgram [13] found in the sample of 24 lead user projects that screening, pyramiding, and signaling remained the most frequently applied search strategies to identify lead users. Hienerth and Lettl [28] explored the measurement of the lead user construct; they considered that social media, data mining, and modern search technologies might be employed to improve the effectiveness of the manual method. These works provide feasible manual methods for scholars to identify lead users in the offline context; however, such methods have some significant shortcomings: time-consuming procedure, high search costs, low sampling efficiency, intense subjectivity, and cannot contact all the lead users in the user space [11,12,29]. Hence, the manual method should be improved to suit the online environment.

2.3. Ordering Algorithm to Identify Lead User

With the rapid development of information technologies, many scholars considered that monitoring social media may replace the manual method to collect the information of customers [22]. They put forward a new method to measure user influence based on the user interaction relationship of a community network from the perspective of user interaction characteristics [30]. Tang and Yang [31] proposed a user-rank algorithm that combined content and network analysis to discover influential members in online communities. Song et al. [32] developed an influence-rank algorithm to identify opinion leaders in blogospheres; their method adopted social networks among community members, which are not always practicable in some online platforms. Hajian and White [33] proposed an index (Magnitude Of Influence (MOI)) to quantify the influence of online social network users on their neighbors, further using the PageRank algorithm to weight the MOI through the influence ranking of neighbors to determine the final influence ranking of the user. Tuarob and Tucker [11] developed a matching algorithm that connected the relationships between lead users and product features to identify lead users with special interests in certain areas. Pajo et al. [12] proposed a classification model to subdivide the users; such a method can reasonably identify the characteristics of different users. To optimize the identification of lead users, scholars have explored the additional features of lead users in the context of online communities. For instance, most lead users are influential and active members in cyberspace. They often generate product-related and service-related content, and their opinions represent most users' perceptions [34,35]. Although the ordering algorithms suggested by the existing works have improved the efficiency of lead user discovery, they have some drawbacks: (1) the definition of lead users in most of these works relates to how the users' views propagate throughout the online platform. In contrast, the lead users in the innovation field should be individuals who have extensive knowledge and unknown demands. That is to say, most of the existing methods are developed to identify opinion leaders [11,13]. (2) Most approaches need network connectivity among members, which is not always available in communities [11]. Thus, the ordering algorithm should be further developed to analyze the characteristics of lead users from the perspectives of knowledge and demand.

3. Method

3.1. Research Framework

The CDC is constructed based on the online forum that motivates users to generate content and interact with other members. Within the CDC, enterprises disclose the design-related problems they face through posts and encourage customers, fans, experts, et al. to contribute (through post image, text, and videos in the community) to settle these design challenges [3]. Additionally, operators also encourage members to post their demands in the forum so that the companies can understand the customers' trends of demand development and initiate new projects of product development [13]. Hence, the CDC users may generate a large amount of content that can reflect their capabilities.

This work develops an identification method that considers multiple characteristics of lead users, including active degree, expertise, and quality of demands. The method contains three steps: first, we develop a criterion system based on previous literature to measure the features of potential lead users; second, text-mining techniques are utilized to collect user-contributed content and user's online behavior statistics from the CDC, and then, we apply the FAHP to evaluate the weight of the indicators and establish the reference sequence of criteria; third, the GRA is employed to calculate the correlation between candidate set (the potential users' indicator set) and reference sequence, and the users are ranked based on their correlations. At last, the top-ranking users (the enterprises decide the scales) will be considered lead users. After these steps, a case study is performed to verify the efficiency of the proposed approach. Figure 1 shows the research framework.

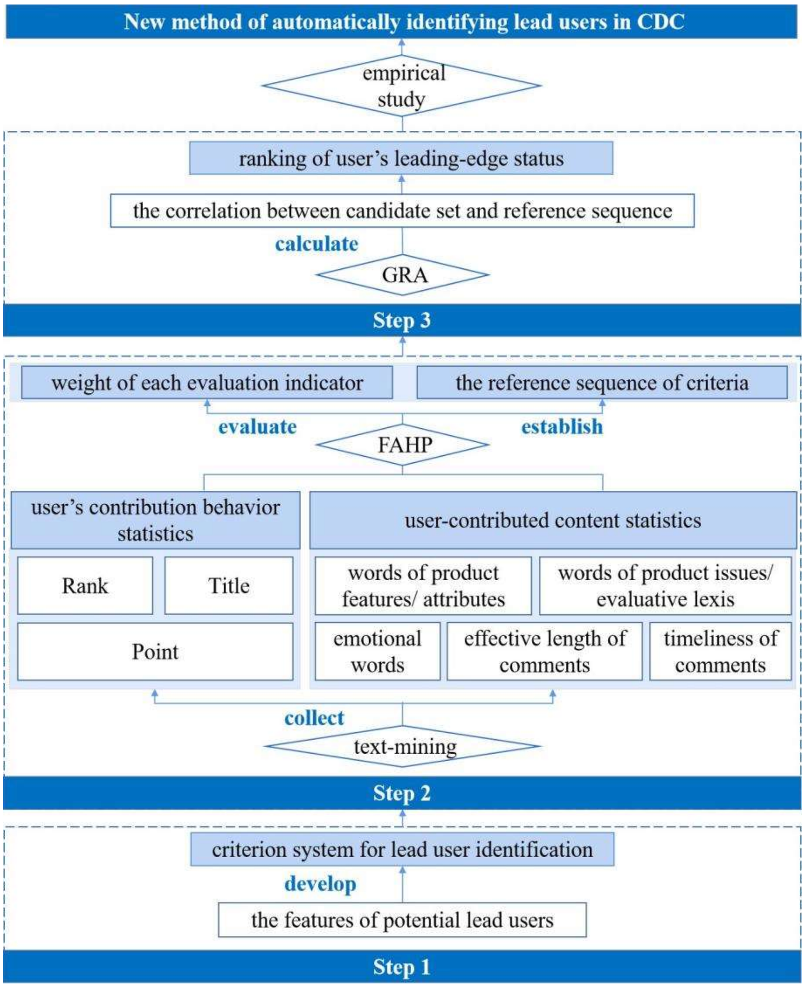

Figure 1. Research framework.

3.2. The Criterion System for Lead User Identification

Since CDC users generate design-related content primarily through posting topics and feedback, the frequency of content contribution and the correlation between content and innovation may reflect the user's leading-edge status [2,12,25,26]. Additionally, some researchers suggested that the user's influence in the community may be a vital characteristic of the lead user [30,36]. However, from the analysis of online innovation platforms (e.g., CDCs and crowdsourcing websites), we noticed that many professional discussion topics posted by users who have extensive knowledge and great skill on technologies and innovation attract very little attention from other members. These users meet the criteria for lead user identification proposed by Hippel, but their visibility in the community is relatively low. Thus, we considered that social attributes (e.g., individual influence) are not the essential features of lead users.

Following previous studies [12,25,26], we employ characteristics of contribution behavior (e.g., contribution frequency) and correlations between user-contributed content and product, innovation, design, and technology as evaluation indicators to measure the individual's leading status. In particular, Guo et al. [3] considered that the ranking system of the online community, which is a kind of statistical tool, can well reflect the features of the users' online behavior. Hence, we apply this system to analyze users' contribution behavior. Besides, text-mining and analysis techniques are utilized to evaluate the relationships between users' contributions and innovation.

3.3. The Calculation of Evaluation Indicators

3.3.1. The Indicators of Features of User's Contribution Behavior

Nowadays, most online communities have developed a ranking system that can reflect the member's reputation, active degree, and community influence by analyzing their online behavior such as posting, replying, likes, sharing, and consumption. The system gives the user a corresponding rank based on the statistics of individual behavior and assists the operator in managing the community. Table 1 shows the introduction of indicators from the standard ranking system.

Table 1. Introduction of indicators from the standard ranking system.

Indicators	Introduction
Rank	The value of user rank.
Title	Virtual honor obtained by users when they reach a certain level.
Point	A behavioral credential that users obtain by using community, browsing, posting, purchasing goods, etc.
Contribution Value	Reflecting the depth of users' participation in online activities.
Virtual Currency	The rewards that users receive through contributing behavior can be used for virtual consumption.

As shown in Table 1, contribution value reflects the depth of community members' participation in online events. In the context of the open innovation platform, this indicator also reflects the breadth and depth of users' expertise and usage experience. A point is calculated based on statistical information of the user's online behavior, which describes the frequency of posting, replying, et al. and reflects the individual's active degree. Rank is a comprehensive reflection of the user's contribution level in the community, reflecting the user's relative position in the member group. These three indicators can well reflect the user's leading-edge status. Therefore, the contribution value, point, and rank are applied to measure the behavior characteristics of users in this work.

3.3.2. The Indicators of Correlations between User-Contributed Content and Innovation

The projects of NPD initiated by the enterprise are mainly carried out around the structure, function, and appearance; hence, the online comments from users that contain these contents are often focused on by the product developers [37]. Users who contribute such content may likely include lead users. Huang et al. [38] considered that the users' highly positive emotional trust affects users' decision-making in virtual communities. Li [39] proposed an ordering algorithm that can be used to evaluate the effectiveness of user comments. He suggested that the individual's reputation, number of thumbs up, timeliness, effective length, words of product features (i.e., attributes), and emotional words may be applied to estimate the correlation between online comments and innovation. Therefore, following prior literature and combining the analysis results of open innovation communities, we utilize product features and issues, emotional words, effective length, and timeliness of comments as indicators to evaluate the user-contributed content. Table 2 shows the introduction and calculation basis of indicators of contribution behavior characteristics and correlations between user-contributed content and innovation.

Table 2. The indicators of criterion system for lead user identification.

Standard Categories	Introduction	Calculation Basis (Indicators)
Features of user's contribution behavior	These indicators can be employed to measure user's interaction level, contribution frequency, product usage, etc., which reflect the individual's active degree and experience.	Contribution value point rank
Correlations between user-contributed content and innovation	These indicators can be utilized to reflect the user's innovation capabilities, expertise, hierarchy, usage experience, etc.	Words of product features/attributes words of product issues/evaluative lexis emotional words effective length of comments timeliness of comments

The quantitative methods for calculating the indicators of correlations between user-contributed content and innovation are as follows.

1. The calculation of indicator of words of product features.

When users post their opinions (such as evaluation, demand, etc.) on products in the community, they often use words of product features to describe them. Attributes reflect the product's inherent characteristics, such as structure, appearance, etc.; most of these words are nouns. Therefore, we considered that when the comments contain product attributes, the comments may reflect product-related content (e.g., use experience, product problems, improvement suggestions, etc.). The more attribute words are included, the more information is transmitted, the more significant the auxiliary role for product development and improvement, and the higher the effective contribution level of users.

This study employs the single comment (i.e., a complete comment) users post as the analysis objects. A self-developed spider tool is used to collect users' comments from CDC, and we apply jiebaR to segment the collected Chinese texts into words and tag them with proper Part-of-Speech (PoS) tags (e.g., noun, verb, adverb, and adjective). After deleting the stopwords and punctuation characters, the comment is transformed into a word set $U_{1i} = (u_{11}, u_{12}, \ldots, u_{1m})$, containing N_w words. The R programming language is utilized to match the words in U_{1i} one by one with the words of product features in a lexicon U_2 developed by the Institute of Computing Technology, Chinese Academy of Sciences [40]. When a word is matched, the number of attributes of the comment is increased by one. We use N_a to represent the number of attributes in a single comment.

2. The calculation of indicator of words of product issues

The words of product issues (i.e., evaluative lexis) are often used to describe consumers' intuitive perception of the product functions, appearance, and other attributes. These words often reflect users' demand expectations and attitudes towards the product. For instance, "too large" in "car fuel consumption is too large" is the user's intuitive feeling towards car fuel consumption. Therefore, when a comment contains words of product issues, the users may post content about the product use experience, product defects, and personal needs. The more words of product issues are included in the content, the more detailed the description of the product problem, and the more profound users' engagement.

The product issues are often described with adjectives and verbs, usually used with adverbs. For example, within the comment "the motor performance is not good," "motor" and "performance" are words of product features; the adverb "not" modifies the adjective "good," and they constitute the word of a product issue. We apply the R programming language to identify the comments' adverbs, adjectives, and verbs. When an adjective or a verb appears in U_{1i}, the number of words of product issues of the comment is increased by one. Additionally, when an adverb appears in U_{1i} together with an adjective or a verb, the number of words of product issues is also increased by one. We use N_i to represent the number of words of product issues in a single comment.

3. The calculation of indicator of emotional words.

When users post their opinions on products in communities, they often express their emotional tendencies through their vocabulary. For instance, "perfect," "good," and "satisfied" express positive emotions, while "bad," "terrible," and "disappointed" express negative ones. The emotion expressed by the users on the functional attributes of the product can be regarded as an open test result for the product [41]. When users express positive emotions, it indicates that the product has satisfied their expectations in a particular aspect. There is no need to improve the product at the moment. However, when users express negative emotions, it indicates that specific attributes of the product have not met their expectations, and the enterprise should improve the product as soon as possible. Positive and negative emotions can reflect an individual's demand tendency and provide essential references for product improvement. Hence, when the comment contains emotional vocabulary, it may reflect the users' product evaluation and demand tendencies. Moreover, the more emotional words are included, the stronger the user's emotional trend is reflected.

We use the R programming language to match the words in U_{1i} with the emotional words in the lexicon U_3 of ICTCLAS [40]. When a word is matched, the comment's emotional words are increased by one. We use N_e to represent the number of emotional words in a single comment.

4. The calculation of indicator of the effective length of comments.

In the Chinese language environment, the length of an online comment is usually quantified by the number of Chinese characters included in the comment. However, most online comments contain a large number of meaningless content, and some of them include numerous characters that have nothing to do with innovation. Thus, we should apply the effective length of the comments to evaluate the leading-edge status of the users. In this work, the ratio of the number of emotional words, product features, and issues in the comment to the number of words in U_{1i} is utilized as the quantized value of the effective length of the comment. Meanwhile, to reduce the deviation caused by the abnormal length (e.g., too long or too short) of comments, the logarithm is used to weaken the difference of the denominator, as shown in Equation (1):

$$P = \frac{\log(N_a + N_i + N_e)}{\log N_w}, \tag{1}$$

5. The calculation of indicator of timeliness of comments.

The timeliness of comments refers to the difference value between the time when the user posts a comment and when the researchers fetch the comment; the smaller the value, the higher the timeliness [39]. The more content the user posts in a period, the higher the user's participation and the higher the user's leading-edge status. For product innovation, the more time-sensitive comments reflect the newer needs of users, and the less likely they are to be discovered and resolved by competing companies.

Meng and Ding [42] suggested that the newer the comments, the higher the credibility. The influential users' effect would diminish with time [43]. Based on the previous study's results, we divide those into two groups: the comments posted in the last three months and those posted three months ago. The former's value is 2, while the latter is 1.

3.4. The Ordering Algorithm of Evaluation Indicators

The identification of lead users is mainly achieved by ranking the leading-edge status of the users. The rules are as follows: the weight of each evaluation indicator is calculated by FAHP. Then, the optimal value of each indicator in the research sample is selected to form a reference sequence, and the correlation between each candidate user's indicator sequence and the reference sequence is calculated by GRA. The greater the degree of association, the higher the user's leading-edge status. Based on the research purpose and requirements, a certain relevance threshold can be set to distinguish between lead users and regular users.

3.4.1. The Calculation of Indicator Weight Based on FAHP

FAHP is a research method widely applied in analyzing and decision-making complex systems [44]. It can simplify complex problems into ordered hierarchical structures. In this work, such a method is used to determine the weights of various indicators. The analysis steps are as follows:

Step 1: Construct a judgment matrix.

The judgment matrix reflects individuals' thinking and judgment; it can be employed to collect the users' opinions on the weight of the indicators. Since the users of the CDC are the analysis objects of this work, the data that constitutes the judgment matrix mainly comes from the network survey of community members. The judgment matrix will be sent to the user's mailbox in a web questionnaire during the investigation process. Then, the members compare and score the importance of indicators according to their experiences and feelings. The scale applied in the matrix is the 0-0.5-1 standard; its descriptions are shown in Table 3.

Table 3. Scale descriptions.

Scales	Definition	Introduction
$a_{ij} = 1$	Important	The indicator *i* is more important than the indicator *j*
$a_{ij} = 0.5$	Equally important	The indicator *i* and indicator *j* are equally important
$a_{ij} = 0$	Unimportant	The indicator *j* is more important than the indicator *i*

a_{ij} is the judgment value.

Step 2: Construct fuzzy consistent matrix.

After constructing the judgment matrix, we utilize the method proposed by Korvin and Kleyle [45] to transform the matrix into the fuzzy consistent matrix.

The rows and columns of the judgment matrix are respectively summed, that is,

$$a_i = \sum_{j=1}^{m} a_{ij},\ i = 1, 2, \ldots, m, \tag{2}$$

$$a_j = \sum_{i=1}^{m} a_{ij}, j = 1, 2, \ldots, m, \tag{3}$$

After summing, transform each element in the matrix, that is,

$$a'_{ij} = \frac{(a_i - a_j)}{2m} + 0.5,\ i,\ j = 1, 2, \ldots, m, \tag{4}$$

Step 3: Calculate indicator weights.

The consistency test is performed to examine the fuzzy consistent matrix, and then the weight wi of each indicator ai is evaluated by the matrix, that is,

$$w_i = \frac{1}{m} - \frac{1}{2A} + \frac{1}{mA} \sum_{j=1}^{m} a'_{ij},\ i,\ j = 1, 2, \ldots, m, \tag{5}$$

In the Equations (2)–(5), m represents the number of indicators. Additionally, in order to improve the resolution of the sorting result, researchers often set $A = (m-1)/2$. Finally, the average values of each indicator weight $W = (w_1, w_2, \ldots, w_m)$ are obtained.

3.4.2. The Ranking of User's Leading-Edge Status Based on GRA

GRA is a multi-factor statistical analysis method [46]. Its basic idea is to determine whether the correlation between multiple sequences and the reference sequence is close and then describe the relationship's size, strength, and order among factors according to the degree of association. For lead users, the greater the value of each indicator, the higher the leading-edge status. Compared with the traditional statistical analysis methods, the advantages of GRA are principally as follows: GRA is analyzed according to the development trend of the research objects. Therefore, there is no excessive requirement for the sample size, and no data are required to have a specific distribution law. The calculation amount is relatively small, and the result agrees with the qualitative analysis result [47]. The analysis steps are as follows:

Step: 1 The dimensionless processing of the data.

$X_k(i)$ and $Y(i)$ represent the user's indicator sequence and the reference sequence, respectively; $k = 1, 2, \ldots, n$, $i = 1, 2, \ldots, m$. n represents the number of users to be ranked; and m represents the number of indicators. Since different indicators often have different dimensions and orders of magnitude, direct comparisons cannot be made, and normalization is required. In the related research of GRA, scholars often use the min–max method for dimensionless processing. However, since the data composition in the criterion system is quite complicated, the magnitude of the difference between the different indicators is enormous, and the min–max method is not applicable in our work. Hence, in order to eliminate the singular data, make the data index in the same order of magnitude, have comparability, and make it suitable for comprehensive comparative evaluation, we employed the averaging method to perform the dimensionless processing to the original data, that is,

$$x'_k(i) = \frac{x_k(i)}{\overline{x_i}},\ k = 1,2,\ldots,n, i = 1,2,\ldots,m, \tag{6}$$

$$y'_i = \frac{y_i}{\overline{x_i}},\ i = 1,2,\ldots,m, \tag{7}$$

$X_k(i)$ is the quantized value of the i-th indicator of the k-th user; x_i is the average value of the i-th indicator of the candidate users' sequence; y_i is the quantized value of the i-th indicator of the reference sequences. The users whose indicator values are the same as the corresponding indicator values in the reference sequence need to be eliminated to avoid invalid results.

Step 2 The calculation of the grey correlation coefficient.

The formula for calculating the grey correlation coefficient is as shown in Equation (8):

$$\xi_k(i) = \frac{\min\limits_{k\in N}\left\{\min\limits_{i\in M}\Delta_k(i)\right\} + \rho\min\limits_{k\in N}\left\{\max\limits_{i\in M}\Delta_k(i)\right\}}{\Delta_k(i) + \rho\min\limits_{k\in N}\left\{\max\limits_{i\in M}\Delta_k(i)\right\}},\ k = 1,2,\ldots,n,\ i = 1,2,\ldots,m, \tag{8}$$

In the equation, $\Delta_k(i) = \left|Y'(i) - X'_k(i)\right|$, $N = \{1,2, \ldots ,n\}$, $M = \{1,2, \ldots ,m\}$. ρ is the resolution coefficient, and its value is taken in the interval [0, 1]. Normally, $\rho = 0.5$.

Step 3 The calculation of grey correlation.

The weighted method is used to calculate the gray correlation, and the formula is as shown in Equation (9):

$$r_k = \frac{1}{m}\sum\nolimits_{i=1}^{m} w_i\xi_k(i),\ k \in N, \tag{9}$$

In the equation, w_i is the value of the indicator weight obtained by FAHP, $\sum\limits_{i=1}^{m} w_i = 1$. Sorting each user's correlation, we can then obtain the ranking of the user's leading-edge status. We are setting the relevance threshold (dynamic) according to the semantic environment and the specific purpose of the research. Then, we can distinguish between lead users and regular users.

4. Empirical Study

4.1. Data Crawling

In this work, a case study of lead user identification is conducted to verify the effectiveness and practicality of our proposed method. We examine the method with samples collected from a CDC, Xiaomi Forum, with over 50 million registered members and about 65 percent active users [3]. Xiaomi is a mobile Internet company focused on designing and manufacturing smartphones; its CDC collects many valuable ideas and designs from community members [2]. Hence, it is an ideal source for the research. Figure 2 shows the user interface of Xiaomi Forum.

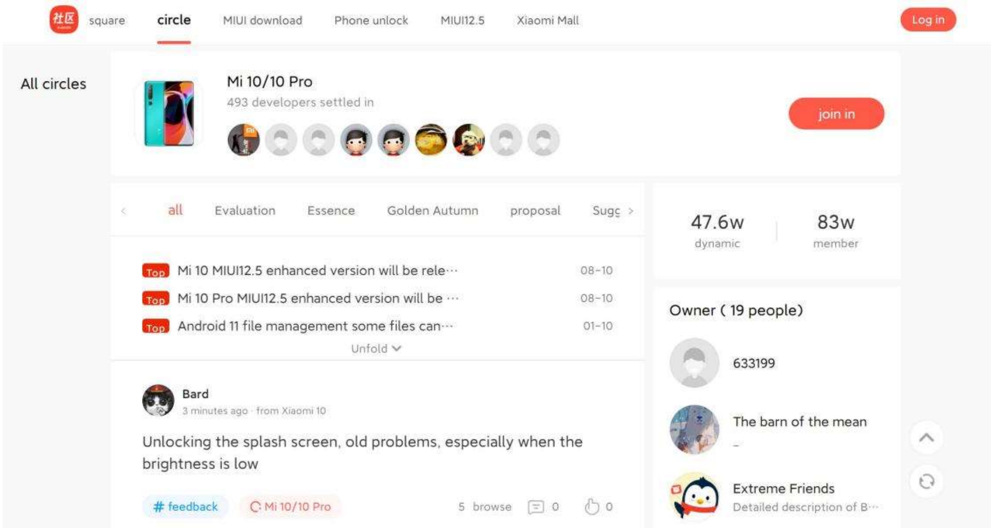

Figure 2. The user interface of Xiaomi Forum (Section of MI10/10 Pro).

We applied a self-developed spider program to collect 9500 users' comments (including topic posts and feedback) and their recent ID information (including contribution value, rank, and point) from 1 November 2018 to 20 May 2019. The R programming language and SPSS tool were utilized to perform the analysis.

4.2. Data Analysis and Results

Among the related comments published by the 9500 users, the maximum number of occurrences of words of product features in the user comments is 1722; the number of words of product issues is 207; and the number of emotional words is 1079. The statistical value is processed by R programming language regarding the effective length of comments; and the maximum quantized value is 0.697. In terms of the timeliness of comments, the maximum average value of all users' posts is 1.7. In terms of the contribution value, the highest value is 11,328. In terms of the rank, the highest value is 8. In terms of the point, the highest value is 213,176. We applied these values as the reference sequence:

$$Y = \{1722, 207, 1079, 0.697, 1.7, 11328, 8, 213176\}$$

Next, based on the data collected through the social survey, we utilized FAHP to calculate the weight of different indicators for lead user identification and then constructed the judgment matrix as shown in Table 4.

Table 4. Judgment matrix.

	1	2	3	4	5	6	7	8
1- Words of product features/attributes	0.500	0.439	0.579	0.694	0.712	0.336	0.285	0.427
2- Words of product issues/evaluative lexis	0.561	0.500	0.873	0.596	0.691	0.341	0.492	0.554
3- Emotional words	0.421	0.127	0.500	0.317	0.606	0.293	0.362	0.481
4- Effective length of comments	0.306	0.404	0.683	0.500	0.637	0.365	0.402	0.346
5- Timeliness of comments	0.288	0.309	0.394	0.363	0.500	0.138	0.144	0.437
6- Contribution value	0.664	0.659	0.707	0.635	0.862	0.500	0.548	0.733
7- Rank	0.715	0.508	0.638	0.598	0.856	0.452	0.500	0.623
8- Point	0.573	0.446	0.519	0.654	0.563	0.267	0.377	0.500

Then, we used Formulas (2)–(4) to convert the judgment matrix into fuzzy consistent matrix, as shown in Table 5.

Table 5. Fuzzy consistent matrix.

	1	2	3	4	5	6	7	8
1- Words of product features/attributes	0.502	0.541	0.448	0.481	0.414	0.585	0.559	0.497
2- Words of product issues/evaluative lexis	0.541	0.575	0.481	0.514	0.447	0.618	0.592	0.530
3- Emotional words	0.448	0.481	0.381	0.415	0.348	0.519	0.493	0.431
4- Effective length of comments	0.481	0.514	0.415	0.450	0.383	0.554	0.528	0.466
5- Timeliness of comments	0.414	0.447	0.348	0.383	0.327	0.497	0.471	0.409
6- Contribution value	0.585	0.618	0.519	0.554	0.497	0.660	0.634	0.572
7- Rank	0.559	0.592	0.493	0.528	0.471	0.634	0.618	0.556
8- Point	0.497	0.530	0.431	0.466	0.409	0.572	0.556	0.488

After the consistency verification of the matrix, the weight value of each evaluation index was calculated by Formula (5):

$$W = (0.126, 0.136, 0.108, 0.117, 0.100, 0.148, 0.141, 0.123)$$

Afterward, we used GRA to calculate the quantitative value of each user's evaluation index, compared the correlation degree between the sequence and the reference sequence, and then realized the user criticality ranking by comparing the correlation degree. Since Hippel considered that only about three percent of customers are lead users [9], we took the top three percent of the 9500 users as the lead user.

To verify the validity of the method set out in the present study, we compared the recognition results of the manual method with our approach. Following the method suggested by Brem and Bilgram [13], we selected 500 Xiaomi Forum users who have used the community for more than one year and sent a survey invitation to them through the mail system. We required them to select the 50 most representative community members based on their feelings and experience. The respondents rated these users in terms of expertise, experience, demand, and participation level (each scored 1/4), and the top 20 users were ranked as the lead users of the community. In order to ensure the effectiveness of the comparison verification, a 60 day online behavior tracking was conducted for these 20 lead users. A total of 272 respondents returned valid information.

These posts were analyzed by seven scholars and technical experts from enterprises/colleges. They found that in addition to the five users ranked 1st, 4th, 10th, 13th, and 19th, the other 15 users had a high leading-edge status. Through the analysis, we found that each of these users posts at least ten topics per week, and most of the posts are related to market, product, and technology. However, although those five users post many topics and are well-known in the community, only a tiny part of their posts are related to technology, market, experience, demand, etc. Therefore, they are just simple active users. As shown in Table 6, the top 10 lead users identified by our method are compared with the lead users recognized by the manual method. The ID in the table is the user's identity number in Xiaomi Forum.

Table 6. Results comparison of the two methods.

User ID	The Users' Correlations Calculated by the Method Proposed in This Work (From High to Low)	The User Ranking Analyzed by the Manual Method
139359812	0.792	3
1069696768	0.756	6
179526422	0.707	5
95572881	0.633	11
437500596	0.622	/
158179452	0.609	8
103017361	0.574	12
139172452	0.518	7
23957255	0.462	/
148869817	0.430	9

/ represents the users who are not in the top 20.

5. Discussion

5.1. Key Findings

The results revealed that the identification method proposed in this study has good precision and recall rate. Besides, it was evident that the comparison showed some differences between the two methods, owing to the manual method being highly dependent on manpower. It takes considerable time to find qualified respondents. Then, in the analysis stage, the participating users will be affected by their own perception and cognitive judgment when selecting the lead user. If there is a lack of interactions between lead users and other users, in this case, their influence is limited, and other users lack a basic understanding of them; such users will not be recognized. According to Table 6, so far as we know, ID 437500596 and 23957255 contributed many product experience posts and product evaluation posts in the community and have a rich user experience and product knowledge. However, due to the relative absence of interactions between these two users and other users, they have not attracted widespread attention, so they have been ignored. Therefore, the manual method needs to carry out cumbersome data processing to reduce the subjective feelings of the survey results. The whole process is complicated, and it is difficult to guarantee the quality of the survey.

Compared with the manual method, the approach suggested by our work mainly uses the contribution content and statistical information retained by the community members to identify the lead users. That is because a series of suggestions and comments generated by user contributions in CDC can generate valuable and novel solutions [48]. Furthermore, the technological progress of machine learning technology for natural language understanding, such as semantic word space model and semantic network analysis, made it feasible to capture open text content on the Internet. In order to overcome the high dependence of traditional lead users identification methods (such as manual screening and ordering algorithm) on manual recommendation, we constructed a criterion system for lead user identification for the field of innovative product design. It can combine with the judgment mechanism of artificial methods and automatically process large-scale data with a machine learning algorithm, without strict requirements for respondents. Therefore, our method has advantages in efficiency and accuracy. It can automatically process large-scale data and has no strict requirements for the respondents. Hence, our method has advantages in terms of efficiency and accuracy.

5.2. Theoretical and Practical Implications

With the application and development of the new generation of Internet and digital technology, economic subjects' interaction models and information matching modes are undergoing profound changes. The integrated development of crowdsourcing and innovative design has quietly subverted the traditional industrial structure. It is the reflection of enterprises on the innovation model. A crowdsourcing design allows enterprises to assign some or all of their design tasks to organizations or individuals with the appropriate capabilities and resources through online platforms and then collaborate to complete the work. It uses a series of means to give play to the wisdom of platform users, sustainably optimizes the allocation efficiency of knowledge resources and technical resources emerging in the implementation of crowdsourcing activities, shortens the response time, and realizes the rapid matching of supply and demand information. It also helps enterprises create better products or services that meet the market and consumers' expectations. Therefore, crowdsourcing significantly improves the efficiency of resource allocation and labor productivity, reduces enterprises' development costs, and promotes the collaborative value creation of crowdsourcing networks.

At present, numerous studies focus on the link between environmental aspects of sustainability and crowdsourcing [49,50]. As a valuable tool, crowdsourcing can successfully attract diverse stakeholders to generate novel ideas and develop these into sustainable solutions [51]. A previous study on the influence of the two sustainability dimensions of environmental and economical on consumer responses found an interaction between consumer support for sustainability and enterprise sustainability [52]. Hence, crowdsourcing could favor an improvement in environmental sustainability performance and economic and social ones. It is worth noting that the digitalization process strengthens the connection between products and factories, the value chains, and users to achieve a production cycle that is as sustainable as possible. Thereby, in the new development stage, business, information, engineering, and analytics perspectives on digitalization are connected [53], which could promote the sustainable development of the digital crowdsourcing economy to support the high-quality development of the economy.

As we mentioned above, this study contributes to research on product design by providing a new method that can automatically discover lead users in CDC. We developed a criterion system that includes the indicators of user contribution contents and online behavior to measure the leading-edge status of the CDC members. Then, an ensemble method that incorporates combination weighting and correlation analysis was constructed to analyze the indicators to search for the lead users. The experiment results confirmed that the proposed method could accurately and efficiently recognize lead users. Additionally, we also explored the characteristics of CDC members' contribution behavior. Since the entire crowdsourcing design process was implemented online, most of the participants' behaviors, such as post topics and feedback, were shown to the community managers. These behaviors can well reflect the individuals' creativity, which may assist enterprises in finding suitable candidates as partners in the NPD projects.

Our study also provides operators with a set of practical implications for the management of CDC and lead user search. First, our method does not need to implement large-scale social surveys, reducing the operators' manpower costs in recognizing lead users. The potential groups of lead users can be automatically identified by the method, and then enterprises may choose suitable collaborators from these groups according to product development needs. Second, the CDC managers can provide the identified lead users with incentives to enhance their loyalty, which may ensure the stability of the NPD projects.

Therefore, our study has significant theoretical value and practical significance. Firstly, inviting users to participate in the design process is the need for innovative product R and D. In the field of open innovation, mobile Internet and the community have realized a crowdsourcing model with multi-role and large-scale social-ecological interaction. Crowdsourcing encourages users to integrate into the development process of innovative products and services, cross-discipline barriers, and quickly obtain users' needs. The participation of more users can enable enterprises to obtain more affluent user needs, which are the traction and driving factors of new product design. The viewpoint of user contribution can guide enterprises to meet design needs and carry out sustainable development continuously.

Moreover, in the era of a knowledge network economy with developed Internet, only depending on the internal resources of enterprises for innovation activities cannot meet and adapt to the growing social market demand. As a critical external knowledge resource, lead users can master the key technology of innovative product design and a large amount of open external knowledge and can have the future demand to produce innovative results. Crowdsourcing provides enterprises with new opportunities to support the integration of lead users. Therefore, recruiting lead users can enable enterprises to obtain extensive and objective innovative ideas, generate more creative cases, and improve new products' innovation quality. Furthermore, they can assist enterprises to achieve sustainable and open innovation.

In addition, the lead user identification method also has a certain degree of applicability in the crowdsourcing platform based on English. Firstly, this method can be extended to the English environment from the operational level. However, it should be attentive to the characteristics of the English language environment. Due to the significant differences between English and Chinese, the evaluation method and judgment mechanism need to be adjusted in combination with the context. In addition, the difference in grammatical structure between English and Chinese leads to the difference in thesauruses between the two languages, so it is necessary to build the corresponding thesaurus in text content analysis. Therefore, after completing the relevant optimization work, the research method proposed in this article can be popularized.

6. Conclusions and Limitations

Lead users are the most valuable customer groups in the NPD. Therefore, accurately identifying and locating lead users is significant for enterprises to effectively organize and manage sustainable open design activities. This study proposes a lead user identification method based on user behavior data and contribution content analysis and constructs a criterion system to evaluate the user's leading-edge status. Our approach has several advantages, such as high efficiency, accuracy, and coverage compared with the manual method. The effectiveness of the proposed method in this work is verified by comparative analysis.

Some limitations restrict this study. The method of the article is to identify lead users by sorting the correlations of the community members. The greater the degree of relevance, the higher the user's leading-edge status. However, selecting the relevance threshold to distinguish between lead users and regular users is not yet clear. Based on Liao's research results [54], we considered that the operators might determine the threshold by two methods: 1. The total amount (S) of valid information in the content contributed by the user can be used as the threshold value. When the user's contributed valid content is more than S, she/he can be regarded as the lead user. The selection of the S value depends on the improvement rate of the product proposed by the enterprise. 2. According to the ranking of correlations, the top F percent of the candidate users are lead users. The selection of the F value depends on factors such as the size of research samples, the extent to which the company intends to improve the product, and the size of the potential customers who may purchase the improved product. Future research may verify these two threshold determination methods and discuss the context in which each method applies.

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