泰国与台湾房地产市场的政治经济分析
THE POLITICAL ECONOMY OF THE REAL ESTATE MARKETS IN THAILAND AND TAIWAN

陳尚懋 [1*], 阎敏琪 [2]
Shangmao Chen[1*] and Minchi Yen[2]

[1,2] 台湾佛光大学公共行政与国际事务学系
[1,2]Department of Public Administration and International Affairs, Fo Guang University, Taiwan
[*]**Corresponding Author, E-mail:** smchen@gm.0fgu.edu.tw

摘要

本研究以政治经济的视角，探讨泰国与台湾房地产市场在近三十年间的发展脉络与政策影响。研究发现，两国房市均受到区域性政治动荡、全球金融危机及疫情冲击的深刻影响。泰国房地产市场经历了金融危机后的低迷、政府刺激政策的复苏、房市抑制措施与疫情冲击，以及后疫情时代的再刺激政策，呈现高度依赖政府政策与外资需求的特征。相较之下，台湾房地产市场则展现出税制改革、金融环境与产业结构变动的影响，并在通膨与资金回流的背景下持续升温。研究指出，泰国房市的波动主要来自外部冲击与政策导向，而台湾房市则受制于税制调整与资金流动。本文透过比较分析，揭示两国房地产市场在政策工具、资金流向与社会结构上的异同，并提供后续政策制定的参考。

关键词: 泰国 台湾 房地产 金融危机 政治经济

Abstract

This study examines the political economy of real estate markets in Thailand and Taiwan over the past three decades. The findings reveal that both markets have been significantly shaped by regional political instability, global financial crises, and the COVID-19 pandemic. Thailand's real estate sector has undergone four major phases: the downturn following the 1997 Asian financial crisis, recovery through government stimulus policies, market cooling measures combined with the pandemic shock, and post-pandemic revitalization strategies. In contrast, Taiwan's real estate market has been influenced by tax reforms, monetary conditions, and industrial restructuring, with inflationary pressures and capital inflows further driving housing demand. The comparative analysis highlights that Thailand's market fluctuations are largely driven by external shocks and policy interventions, while Taiwan's market dynamics are more closely tied to fiscal reforms and capital mobility. This study contributes to understanding the similarities and differences in policy instruments, financial flows, and social structures between the two markets, offering insights for future policymaking.

Keywords: Thailand, Taiwan, Real Estate Market, Financial Crisis, Political Economy

引言

2025年，我在泰国曼谷完成了人生第一次的海外购屋。从找中介、看房、斡旋杀价，到最终签约过户的过程，不仅让我亲身体验了泰国房地产市场的运作模式，也深刻感受到市场低迷时期的氛围(*Thai Property Slumps to 7-Year Low, Luxury Homes Pile Up*, 2026) (Thai Condo Market in 2026, 2026)。当时泰国房市因疫情后经济复苏不振、利率上升与外资退场而陷入盘整，许多屋主因贷款压力而抛售房产，形成价格下修的趋势，也因此让我小捡了个便宜。与此同时，我也在台湾宜兰决定出售自宅，但同样亲身体验到房市冷清的现象，买卖历经数月乏人问津。根据媒体报导，2025年全台建物买卖移转量仅约26.16万栋，年减25.4%，创下近九年新低。同时这是史上第三低交易量，仅高于2016年房地合一税上路与2001年网络泡沫时期(经济日报, 2026)。泰国与台湾房地产如此的「双低潮」现象，成为我进一步研究两地房地产市场政治经济的契机。

房地产市场的波动，往往不仅是经济指标的反映，更深层地牵涉到政府政策、国际资金流动、社会结构与政治稳定等多重因素(Khumpaisal, 2011)。泰国房市高度依赖政府刺激政策与外资投资，市场波动与政治动荡、国际资金流动密切相关；相较之下，台湾房市则深受税制改革、金融环境与产业结构转型的影响，并在通膨与资金回流的背景下持续升温。

本文试图以政治经济的分析视角，探讨两地房地产市场在近三十年间的发展阶段，包括：政策工具与外部冲击之间的互动关系，并透过比较分析揭示其异同。透过结合个人购屋与售屋的田野经验与宏观政策研究，本研究不仅有助于理解两国房市的历史脉络，也能为未来政策制定提供理论基础与实务参考。

内容

本文将先介绍泰国与台湾房地产两地自1997年亚洲金融风暴以来，将近三十余年的发展。首先，在泰国房地产发展方面，大致可以分为四个阶段：

1. 金融危机的爆发（1997-2001）

1997年7月2日爆发的亚洲金融危机，对于泰国造成极为严重的影响，层面从初期的金融危机，银行倒闭连带也影响许多企业的经营，造成经济危机；过多的失业人口因而产生社会危机，一连串的问题也对泰国的房地产市场造成致命性的打击(Calhoun, 2001)。在危机爆发初期（1997-1998年），市场出现大量烂尾楼与空置房舍，政府不得不采取非常手段予以协助。当时执政的新希望党（New Aspiration Party）总理昭华立（Chavalit Yongchaiyudh）便靠着其军事将领的背景，要求国防部购买位于曼谷郊区卫星城市蒙通他尼（Muang Thong Thani）大量空置房舍，作为军事人员宿舍和办公室。并且规划高速公路以连接当地，试图透过改善交通来提升该区域的房产价值和消化速度(SHENG, 2002)。

2. 后金融危机时期的刺激政策（2002-2018）

随着经济逐渐稳定，2001年上台的泰爱泰党（Thai Rak Thai Party）总理塔克辛（Thaksin Shinawatra）政府，于2000年代初期推出了具体的政策来解决贫困人口的住房问题，希望藉此能刺激房市的交易。首先是2003年推动的「关怀之家计划」（Baan Eua-Arthorn），由国家住宅局（National Housing Authority, NHA）主导，目标是在2003至2007的五年期间兴建60万户低价住宅。买家先与NHA签订5年的「租购合约（Hire-purchase）」，若缴款纪录良好，则可转由政府住宅银行（Government Housing Bank, GH Bank）提供长达30年的低利房贷，由租转购。其次也是2003年小区组织发展研究所（Community Organization Development

Institute, CODI）所推出的「安居计划」（Baan Mankong），针对贫民窟进行就地升级或重建，提供政府贷款和补贴，让小区自行管理开发，总计共有超过 5 万 4 千多中低收入户受惠 (Kojima, 2013)。

除了上述社会住宅政策外，当时泰国政府推动的主要房市刺激政策，尚有：

金融支持与信贷放宽政策：透过政府住宅银行提供低于市场的房贷利率，迫使商业银行跟进降低利率，大幅提升了民众的购屋负担能力。另外，由于高价房产市场饱和且受创严重，低利政策也成功引导开发商转向兴建中低价位的住宅，满足了新兴中产阶级的购屋需求 (Sheng, 2002)。

税收优惠与投资奖励：为鼓励开发商兴建中低价位或是社会住宅，投资促进委员会（Board of Investment, BOI）提供开发商 3 至 8 年的企业所得税豁免；针对购买 500 万泰铢以下房产的首购族，政府允许其在 5 年内享有房价 10% 的个人所得税抵免等；透过政府住宅银行推出针对首购族的「0% 利率贷款（前三年）」及放宽贷款成数（Loan-to-Value Ratio, LTV）可达 100%，导致民众购房意愿大增，申请量爆满 (Kojima, 2013)。

泰国政府后续于 2016 年推出「泰国 4.0」（Thailand 4.0）经济战略，并于 2017 年大力推动攸关往后 20 年发展的东部经济走廊（Easten Economic Corridor, EEC），也因而带动了春武里（芭堤雅）等地的土地与房产需求，是疫情前推升房价的主要国际层面动力之一(赖裕富 2018)。加上 2013 年中国推出的一带一路政策，也增加了中国投资者对于泰国房地产的兴趣(Fan 等 2021)。透过政府相关政策的协助下，进入 2010 年代，泰国房地产市场开始出现复苏迹象，尤其是首都曼谷地区。随着曼谷捷运（BTS/MRT）扩张及中国投资者（留学、养老、避险）的大量涌入，曼谷的公寓（Condo）市场出现爆发式增长(Srivarasat & Wongsurawat, 2019)(Fan et al., 2021)(Saguansap et al., 2025)，也引发了市场对「房地产泡沫」的担忧

3. 房市抑制政策的介入与 COVID-19 疫情的爆发（2019-2021）

为了抑制家庭债务攀高与房地产投机行为，泰国中央银行开始祭出严厉的降温措施。首先是 2019 年推出的限贷令，强制要求第二间房或高价房产（1000 万泰铢以上）需准备 10%-20%的头期款，较之前相比严格限制了贷款成数(Kojima, 2013)(Khumpaisal, 2024)。其次则是 2020 年推出新的土地和建筑税（Land and Building Tax），以取代先前旧的房屋税，对土地和建筑物征收累进税率，特别针对空置土地与建物课征重税（每三年增加 0.5%）(Srivarasat & Wongsurawat, 2019)。许多地主或建商为了避税，在 2019-2020 年在市场需求疲软时，将大量土地抛售或进行开发，造成了价格竞争。另外，为了防止短期炒作，也有明文规定若在持有房屋 5 年内出售，需缴纳 3.3%的特种商业税（Specific Business Tax）(赖裕富, 2018)。此举有效打击了投机客，但也导致购买力下降。数据显示，在疫情爆发前的 2019 年，房地产市场已经因为 LTV 政策和新土地税的实施而开始收缩，许多买家因无法获得全额贷款而放弃购房 (Kuen-wei et al., 2025)(Khumpaisal, 2024)。正当市场因 LTV 政策而降温时，COVID-19 疫情的爆发造成了「双重打击」。先是因为疫情导致国门关闭旅游业崩盘，疫情导致旅游业崩溃，高度依赖外国买家（特别是中国买家，占外国需求大宗）的公寓市场首当其冲。2020 年外国人购买公寓的总量下降了三至四成。因为疫情造成的需求减少，也导致房地产价格下跌，尤其是曼谷地区的公寓。同时，市场需求出现结构性变化，从市中心的公寓转向郊区、空间较大的低层住宅（透天/别墅），以适应居家办公的「新常态」。更值得注意的是，消费者开始关注结合医疗与健康养生的房地产项目，特别是在清迈与曼谷周边(Zhai et al., 2024)(Mingwei Huanga and Pawares Funo, 2024)(Sakulsinlapakorn, 2023)。

4. 后疫情时代的再刺激政策（2022–）

后疫情时代，透过网络营销或在线看房的新型态也对于泰国房地产交易造成影响(Shinasharkey & Wattanasiri, 2024)。为了在后疫情时代复苏经济并重振房地产信心，泰国政府再次祭出刺激政策，而其中的重点之一在于「吸引高资产外国人」，于 2001-2002 年推出长期居留签证（Long-Term Resident Visa, LTR visa）。根据研究显示，LTR 签证放宽期间与房地产价格呈现正相关，显示该政策成功刺激了外资需求，对于房地产复苏小有贡献(杜娟 2024)。随着台泰两国的交流日趋热络，台湾投资者也对于泰国房地产表达出高度的兴趣，并且成为泰国房地产市场中的重要买家(Hsuting, 2025)。尽管如此，泰国房地产在 2025 年仍呈现出低迷态势。

其次，台湾房地产发展同样也可分为四个阶段：

1. 经济衰退期（1997–2003）

1997 年亚洲金融危机爆发，台湾虽未如韩国、泰国及印度尼西亚等国遭受毁灭性重创，却为后续经济体质的转变埋下伏笔，当时新台币兑美元汇率由 27.9 元一路贬至 32 元大关（数据源：中央银行全球信息网），尽管贬幅相对轻微，但邻国货币的大幅竞贬，导致台湾出口产品失去价格竞争力，使外销产业面临严峻挑战(连文荣, 1998)。在国际动荡余波未平，内部环境更接踵而至，1999 年发生 921 大地震，根据行政院主计总处统计，灾损高达新台币 3,647 亿元，重创国内整体经济基础，对后续经济发展产生深远影响。为振兴低迷已久的房地产市场，政府于 2002 年实施「土地增值税减半」政策作为诱因，该政策确实有效刺激了沉寂多时的交易量(汪瑞芝(Jui-Chih Wang) et al., 2005)。然而，正当房市初见复苏曙光之际，2003 年初爆发的 SARS 疫情再度重挫市场信心，使经济与房市陷入另一波短暂的挫败(徐世勋 et al., 2007)。

2. 景气复苏期 2004–2014

经历 SARS 疫情的低迷，台湾房地产市场 2004 年进入复苏的周期。在国际方面，美国联准会（Fed）长期维持低利率环境，使资金流动充沛；特别是 2008 年全球金融海啸后，各国推动量化宽松政策（QE），使得过剩的资金转向保值资产，因而奠定了台湾房市攀升的基调。在国内政策方面，政府于 2009 年将遗产及赠与税调降至 10%，成功诱使大量海外资金回流并投入房地产；同时，随着 ECFA（两岸经济合作架构协议）的签署(谢正一 & 吴毓星, 2010)，两岸和平红利的预期心态转化为投资动能，促使不动产的交易热度持续攀升，也因台湾房价快速飙涨，政府于 2011 年 6 月正式实施《特种货物及劳务税》（俗称奢侈税），规定持有房地产未满两年转手需课征 10% 至 15% 的奢侈税，此政策上路造成交易量的下滑(王进祥, 2013)，但也进一步强化了房地产作为「长期资产配置」的属性，市场资金则更趋向长期持有或增值潜力区块。2012 年 8 月启动之实价登录，借由成交价之透明化，打破长期以来的信息不对称，这两项政策也构成政府治理房市之连环配套 (王进祥, 2012)。

3. 税制盘整期（2015–2019）

2015 年之交界，房地合一税 1.0 正式实施前引发了前所未见的交易量震荡(徐俊贤 & 庄荞安, 2015)。2015 年 12 月全台买卖移转栋数冲上历史高点，主因为买卖双方力求在旧制截止前完成过户以减轻税负，导致税制上路当年第一季量能随即腰斩，房地产交易量明显萎缩；然而 2018 年美中贸易战爆发，全球供应链面临重组的压力，中国经济也因此放缓(纪博栋, 2019)，这促使海外台商纷纷寻求资金外移，这股压力意外催生了资金回流台湾，这段时期的房地产特色在于：国内税制虽试图压抑投机，但全球地缘政治的动荡却意外为台湾房市注入了新的复苏动能的特殊局面。

4. 通膨膨胀后再管制期（2020–）

2020 年 COVID-19 疫情引发全球供应链断链与物流受阻，导致建筑营造成本面临工料双涨(刘泰仪 et al., 2020)；随后各国采取货币宽松政策（QE）引发全球性通货膨胀，因不动产具备抗通膨属性，吸引大量避险资金涌入。另一方面，受惠于全球供应链重组，台积电于台南、高雄等地的扩厂计划，不仅带动高薪就业机会，更引发房地产由传统精华区流向中南部的「补涨效应」(方钰蓁, 2025)。面对过热的市场，政府虽于 2021 年实施房地合一 2.0 意图打击投机(张芷 & 林健生, 2021)，然而 2023 年推出的新青安贷款，因提供优渥利息补贴与延长宽限期，意外在需求端注入强大购买力，导致房价再度推向历史高点。进入 2024 年下半年，市场遭遇了双重资金封锁。首先，由于新青安引发的抢购潮导致银行放款过度集中，各大银行因触及《银行法》第 72-2 条的不动产放款水位红线，而实施限贷令。随后，央行为了进一步冷却市场预期，于同年 9 月重启第七波选择性信用管制，其力道最为剧烈，也迫使市场在 2025 至 2026 年间进入资金紧缩的冷静盘整期，交易量显着萎缩。

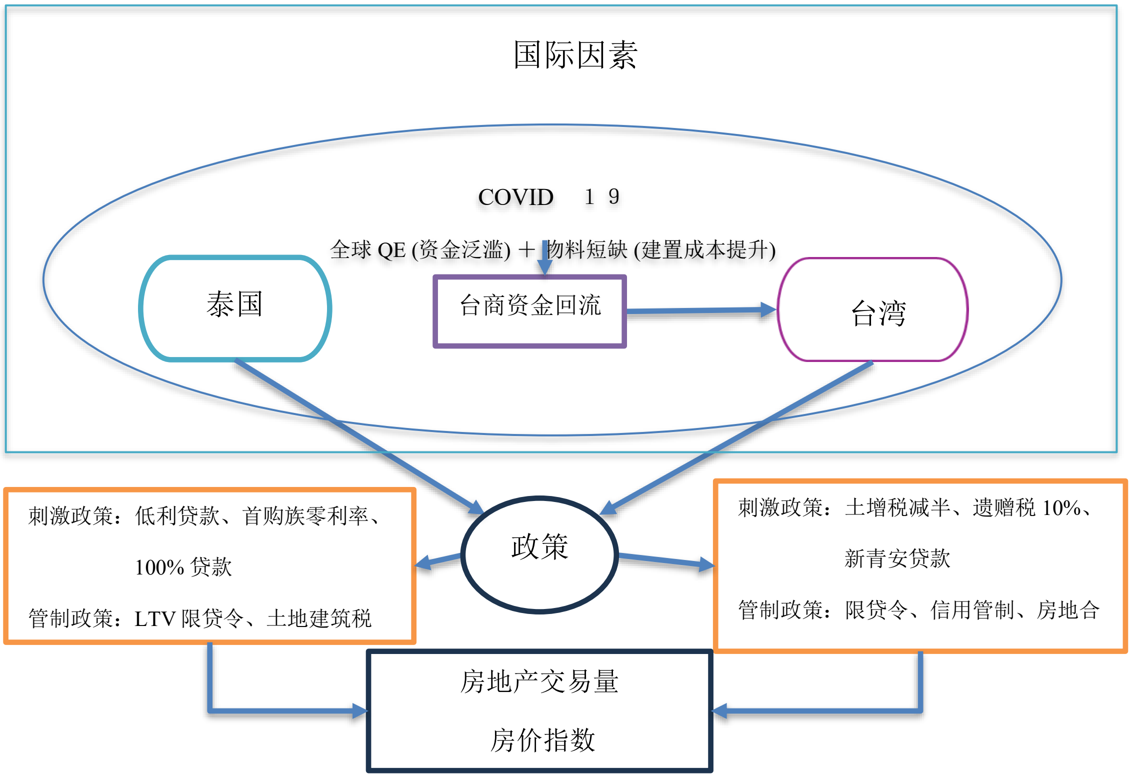


图 1: 台湾与泰国房地产发展

来源: 作者自行绘制

总结

而后从 2000 年代初期开始，开始出现有利的国际因素，例如：全球景气复苏，在美国主导下的低利率与量化宽松政策，加上中国一带一路推动，大批过剩资金外溢至泰国，以及两岸因 ECFA 签署带来的平和红利，都有利于两国的房地产发展。加上两国也纷纷推出相关鼓励政策：泰国透过 GH Bank 提供低利贷款、首购族前三年 0%利率，并放宽贷款成数至 100%。

同时推动基础建设（捷运）、东部经济走廊（EEC）与投资优惠，房市快速成长，泰、台两国从2000年初期至中期皆有一段将近长达十年的黄金繁荣期。

泰国从2002年开始交易量逐渐上扬，从已登记权利之规费来看，从2002年的5,314.92百万泰铢，上升至2003年的8,739.94百万泰铢，上升幅度达64.44%，随后更上升至2018年的最高点22,778.10百万泰铢。泰国连续几年的上涨主因是政府为解决低收入户族群住房问题，放宽贷款成数而刺激买气；另一项政策是允许外国人持有公寓总楼地板面积的49%，这吸引了大量外国资金进场，虽然在2008年遇到金融海啸造成2009年房产移转数量骤减，但此现象影响并没有维持太久，2014年后政局转稳，吸引不少外资购买意愿，甚至曼谷新成屋移转数高达133,439户。而台湾政府为振兴房市当时推出1.8兆元优惠房贷，并透过调降土地增值税与遗赠税等政策，成功吸引海外资金回流。2003年SARS疫情结束后，房市随即展开报复性反弹；至2006年，全台建物买卖移转栋数更冲上45万户，创下1997年金融风暴以来的新高点。

然而从2010年代中期过后，国际上出现些许对于房地产不利之因素，包括：美中贸易战、全球供应链重组、中国经济放缓，以及COVID-19疫情，造成市场不确定性升高。同时也因为房市过热，台泰两国政府接推出若干降温政策：政府开始收紧政策，限制贷款成数（LTV限贷令）、提高土地建筑税，并对空置土地课征重税（每三年增加0.3%），以抑制投机与过度囤地。台湾政府推动奢侈税（2011）、实价登录制度（2012）、房地合一税1.0（2016），强化市场透明度并抑制炒作，房市进入修正与降温阶段。

根据数据显示，泰国房地产权利登记规费从2019的20,145.11百万泰铢，骤降至2020年的15,776.02百万泰铢，幅度高达21.69%；随后又逢COVID-19疫情爆发的双重打击，导致曼谷新成屋移转登记数连续多年递减，投机资金明显撤离市场。与此同时，台湾房市在连番政策重压下，于2016年全台建物买卖移转栋数骤降至24.5万栋，不仅一举跌破2001年网络泡沫时期的25.9万栋纪录，更创下近三十年来的历史新低。这项数据验证了加税与限贷政策对投机需求的强力压制。

2019年Covid疫情的爆发，让泰台两国的房地产发展出现些许差异。在后疫情时代，泰国政治持续动荡，加上军政府执政时期推出的东部经济走廊并未搭上半导体供应链，以至于经济持续低迷，连带也影响房市发展，泰国的房地产发展陷入前所未有之低迷。反观台湾因为被纳入全球半导体供应链，加上台商从大陆撤资大量回流，使得台湾的房价在疫情与后疫情时代不降反增。原本政府推出想要协助年轻人购屋的新青安贷款，也成为有心人士投机炒作房市的工具。也使得政府被迫推出第七次限贷令与央行信用管制，搭配房地合一2.0，持续抑制投机，让市场在复苏中保持稳健。

泰国在进入后疫情时代，虽然在曼谷地区并未受到太大影响，2024年的新建案仍维持在97,129，但在全国的登记权利规费方面则从2022年的15,804.30百万泰铢，下降至2024年的14,036.04百万泰铢。反观台湾，房价指数在疫情之后持续上升，从2020年的92.7375升至2025年的161.88，成长幅度相当惊人。在建物买卖移转栋数从2020年的32.7万栋，增加至2021年的34.8万栋。尔后随着政府的打房措施出炉，2025年全台最终仅剩26.1万栋，较2024年的35.1万栋大幅萎缩25.5%。这项数据不仅刷新了台湾房市史上「单年最大衰退纪录」，更具体验证了金融管制政策对市场流动性的强力压制。泰台两国房市虽呈现不同的病征——泰国是因「购买力透支」而失灵，台湾则是因「政策断金流」而停滞，但两者皆在2025年步入了极度低温的市场寒冬。

表 1: 泰国与台湾房地产发展之影响因素

	国际因素	**泰国国内政策**	**台湾国内政策**
第一阶段 **危机重创** **1997-2000 年代初期**	亚洲金融危机 网络泡沫化 美国 911 事件 SARS 疫情冲击亚洲	1997-2002	1997-2003 实施土增税减半(2002) 推动优惠房贷 修正《不动产证券化条例》(2003)
第二阶段 **黄金繁荣期** **2000 年代初期-2010 年代中期**	一带一路 全球景气复苏 美国 Fed 维持低利率 QE ECFA 签署之两岸和平红利(2011)	2003-2018 成立资产管理公司 GH Bank 低利贷款 低收入户的住房计划 首购族 0%利率（前三年） 放宽贷款成数（LTV 可达 100%） EEC、基础建设（捷运） BOI 优惠	2004-2014 遗赠税降至 10% 诱使海外资金回流(2011)
第三阶段 **修正与急冻期** **2010 年代中期-2010 年代末 2020 年代初**	COVID-19 美中贸易战 全球供应链重组 中国经济增速放缓	2019-2021 LTV 限贷令 土地建筑税（增加持有与购买成本）空置土地课征重税（每三年增加 0.3%）	2015-2019 房地合一税 1.0(2016) 奢侈税(2011) 实价登录(2012)
第四阶段 **再刺激与复苏** **2020 年代初期至今**	地缘政治 全球通膨	2022- 转让费用与抵押贷款费用减免 放宽 LTV 限制（暂时性） LTR 签证	2020- 新青安贷款(2023) 第七波限贷令(2024) 第七波央行信用管制(2024) 房地合一 2.0、

来源: 作者自行整理

表 2: 泰国与台湾房地产发展之相关数据

年度		**1997**	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**
泰国	房价指数	144	141	127.1	131.2	130.9	131.8	135.7	143	154.4	160.2	162	160.2	157.6	158.1
	曼谷新建案	151,880	65,742	31,944	38,582	32,650	37,833	56,040	69,101	71,713	79,757	75,530	85,579	94,977	106,893
	登记权利规费（单位：百万泰铢）	6,778.92	4,182.28	3,579.63	3,437.71	3,783.97	5,314.92	8,739.94	10,635.26	11,752.60	11,102.78	11,121.38	8,167.50	6,199.17	10,922.92
台湾	房价指数	n.a.	n.a.	n.a.	50.08	48.35	44.80	45.35	48.49	49.82	53.00	58.62	61.94	59.98	68.12
	建筑物买卖移转登记数	466,568	385,969	385,074	321,165	259,494	320,285	349,706	418,187	434,888	450,167	414,641	379,326	388,298	406,689

年度		**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**	**2024**	**2025**
泰国	房价指数	100.5	103.8	111.8	122.5	131.1	137.2	141.2	148.3	149.5	154.8	158.2	162.7	168.2	171.6	174.7
	曼谷新建案	81,856	125,002	132,302	133,439	123,830	126,543	114,503	130,835	117,965	112,040	80,837	96,547	99,370	97,129	n.a.
	登记权利规费（单位：百万泰铢）	14,585.25	17,016.35	20,221.81	19,381.67	16,154.49	15,647.88	21,148.31	22,778.10	20,145.11	15,776.02	16,616.34	15,804.30	19,030.82	14,036.04	n.a.
台湾	房价指数	75.07	79.57	88.01	92.02	89.15	73.62	76.75	80.08	85.91	92.74	98.94	128.65	135.92	151.83	161.88
	建筑物买卖移转登记数	361,704	328,874	371,892	320,598	292,550	245,396	266,086	277,967	300,275	326,589	348,194	318,101	306,971	350,525	261,601

来源: 泰国中央银行、台湾内政部不动产交易平台

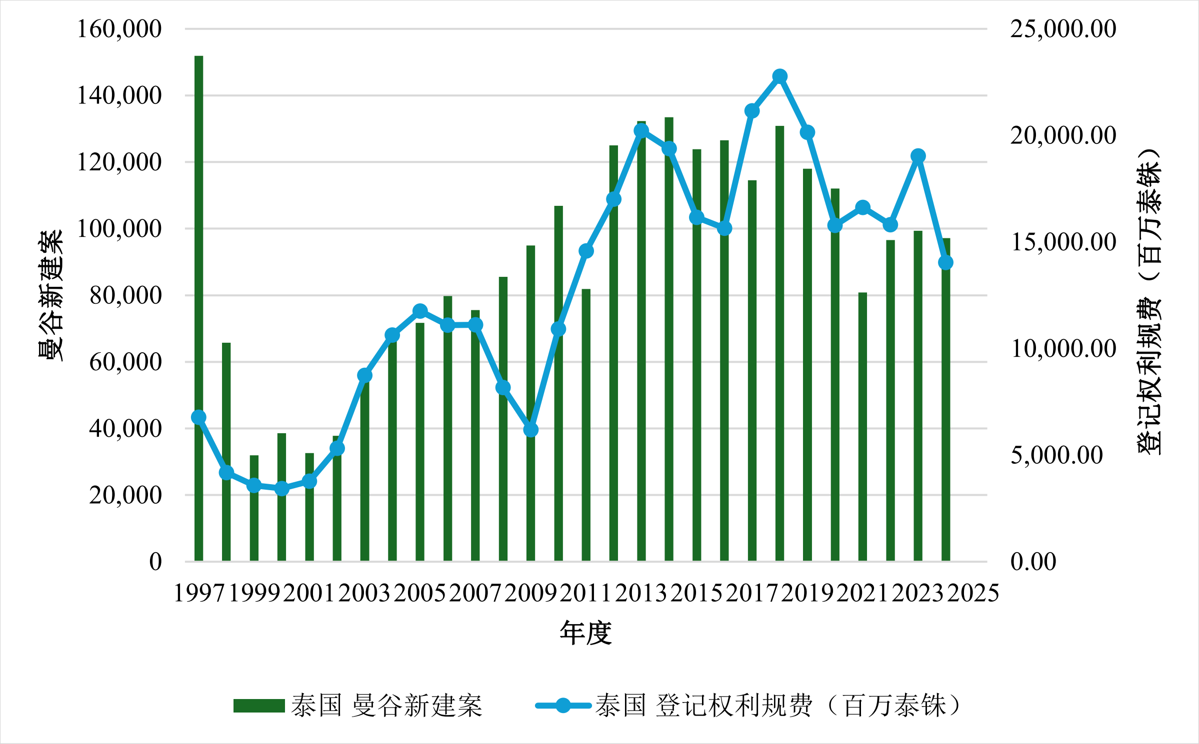


图 2: 泰国房地产市场趋势分析（1997-2025）

来源: 泰国中央银行

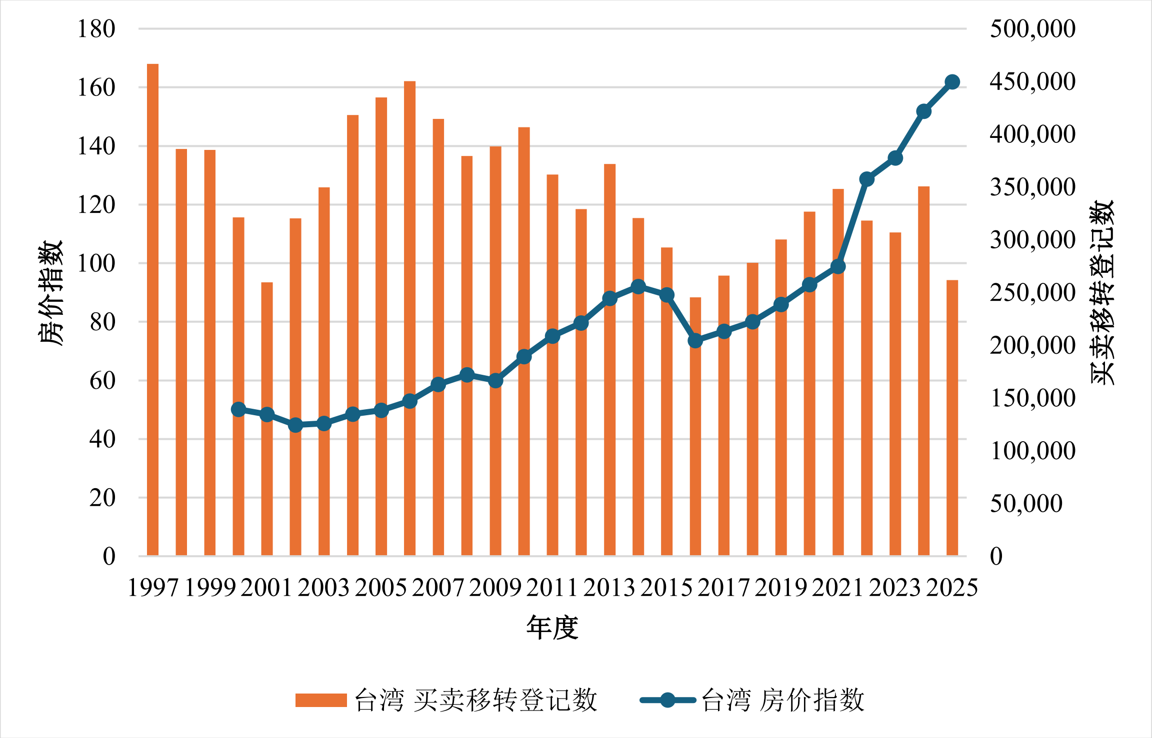


图 3: 台湾房地产市场趋势分析（1997-2025）

来源: 台湾内政部不动产交易平台

建议

在分析完泰国与台湾房地产历程之后，以下将分别针对两国往后的房地产发展提出建议。首先在泰国方面，将分为几个层面探讨：

1. 政策面

泰国政府应加强房市透明度，可考虑采取台湾的模式，建立更完善的实价登录制度，避免信息不对称。同时降低对短期外资的依赖，并且强化长期签证友善制度，吸引长期投资者（如退休移民、跨国企业员工），提升市场稳定性。

2. 结构面

房地产发展应与产业升级挂钩，例如结合数字经济、医疗健康、教育产业，避免单纯依靠观光或基础建设。2 月 8 日大选过后的新政府必须要能推出符合现今国际政经发展情势的政策，东部经济走廊（EEC）若要持续推动，需与全球供应链（如半导体、绿能产业）接轨，才能带动房市需求。

3. 市场面

过去曾经推行过的政策应持续进行，例如：加强对空置土地与投机行为的管制，避免资源闲置。并推动中小型住宅与社会住宅，满足中产阶级与年轻族群的需求，避免市场过度集中在豪宅与投资型产品。

其次在台湾方面，同样也将透过三个层面提出建议：

4. 政策面

新青安贷款本意良好，但应设计更严格的资格审查机制，避免成为投机炒作工具。房地合一 2.0 与限贷令应持续执行，但同时要兼顾自住族群的购屋需求。

5. 结构面

台湾进入后疫情时代的这几年来，房市过度依赖半导体产业带来的资金回流，应推动多元产业发展，避免单一产业波动影响房市。另外则是政府应协助加强都市更新与老屋改建，提升居住质量，让房市成长与城市发展结合。

6. 市场面

应建立更完善的房价指数与交易量监测机制，让政策制定更精准。且推动「区域平衡」发展，避免台北、新竹或是随着台积电设厂等地房价过度飙升，而其他县市房市低迷。

短期来看，台湾应需防止房市过热与投机，泰国则需要避免房市长期低迷并吸引稳定需求。长期来看，泰国与台湾两国都应该让房地产回归居住本质，而非纯粹投资工具。为此必须建立并强化公开交易信息平台，提升市场信任度。两国都应该让房地产发展与产业结构升级、居住需求相结合，才能走出「繁荣—修正—复苏」的循环，迈向更稳健的长期发展。

参考文献

Calhoun, C. A. (2001). Property Valuation Models and House Price Indexes for the Provinces of Thailand: 1992–2000. *Housing Finance International*, *17*(3), 31–41.

Fan, Z., Loahavilai, P., Chakpitak, N., & Rattanadamrongaksorn, T. (2021). Growing Properties Investment in Thailand Based on Fuzzy Analytic Hierarchy Process. *International Journal of Trade, Economics and Finance*, *12*(6). https://doi.org/10.18178/ijtef.2021.12.6.712

Hsuting, C. (2025). *The Influencing Factors of Decision to Invest in Thailand's. Real Estate Market: The Case of Taiwanese Investors* [MASTER OF BUSINESS ADMINISTRATION]. SIAM UNIVERSITY.

Khumpaisal, S. (2011). Analytic Approach to Risk Assessment in Thailand's Real Estate Development Industry [Ph.D., Liverpool John Moores University (United Kingdom)]. In *PQDT - UK & Ireland*. ProQuest Dissertations & Theses A&I (1779950236). http://libautorpa.fgu.edu.tw:81/login?url=https://search.proquest.com?url=https://www.proquest.com/dissertations-theses/analytic-approach-risk-assessment-thailands-real/docview/1779950236/se-2?accountid=10831

Khumpaisal, S. (2024). A Qualitative Perspective to Analyse External Risks Impact on Thailand's Real Estate Sector. *Pakistan Journal of Life and Social Sciences (PJLSS)*, *22*(2). https://doi.org/10.57239/PJLSS-2024-22.2.001501

Kojima, T. (2013). Thailand's Growing Housing Loan Market. *Nomura Journal of Capital Markets*, *5*(1), 1–11.

Kuen-wei, S. D. T., Woei-Chyi, C., Chin-Tiong, C., Kim-Wing, A. C., & Khai-Shuen, P. (2025). A Review of COVID-19 Impacts on Global Residential Property Prices and Key Trends: UK, China, Malaysia, Singapore and United States. *International Journal of Research and Innovation in Social Science*, *VIII*(XII), 2038–2059. https://doi.org/10.47772/IJRISS.2024.8120172

Mingwei Huanga and Pawares Funo. (2024). Choice for rigid demander investing in real estate outside of China: Thailand or Malaysia? *Mingwei Huanga and Pawares Funo*, *11*(1), 1–13.

Saguansap, V., Wongbumru, T., Saguansap, P., Mruksirisuk, P., Chaipong, S., Veerasilp, W., & Thanvisitthpon, N. T. (2025). Factors influencing housing rental decisions across major cities in Thailand: An analysis of marketing mix elements. *Sustainable Futures*, *10*, 101196. https://doi.org/10.1016/j.sftr.2025.101196

Sakulsinlapakorn, K. (2023). The Roles of Reference Group towards the First-Time Homebuyers' Purchase Decision of Wellness Real Estate in Bangkok, Thailand. *Asian Journal of Business Research*, *13*(3), 92–113. https://doi.org/10.14707/ajbr.230159

SHENG, Y. K. (2002). Housing, the state and the market in Thailand: Enabling and enriching the private sector. *Journal of Housing and the Built Environment*, *17*(1), 33–47. JSTOR.

Shinasharkey, T., & Wattanasiri, N. (2024). Marketing Mix and Real Estate Purchase Intention through Social Media Channel. *AU E-Journal of Interdisciplinary Research*, *9*(2), 20–26. ProQuest Central Premium; Publicly Available Content Database (3152434113).

Srivarasat, P., & Wongsurawat, W. (2019). The Bangkok Housing Market: Past Performance And Future Prospects. *Journal of Applied Business Research*, *35*(1). https://journals.klalliance.org/index.php/JABR/article/view/235

Thai condo market in 2026: A year of cautious selection as new projects decline. (2026, January 23). Nationthailand. https://www.nationthailand.com/business/property/40061601

Thai property slumps to 7-year low, luxury homes pile up. (2026, January 17). Nationthailand. https://www.nationthailand.com/business/property/40061353

Zhai, F., Dawod, A., Chanaim, S., & Suyaroj, N. (2024). A New Perspective on Real Estate in Thailand in the Post-Epidemic Era: Multi-Criteria Decision AnalysisUna nueva perspectiva del sector inmobiliario en Tailandia en la era posepidémica: Análisis de decisiones con criterios múltiples. *Apuntes Del Cenes*, *43*, 155–172. https://doi.org/10.19053/uptc.01203053.v43.n78.2024.17278

王进祥. (2012). 实价登录与税制改革. *土地问题研究季刊*, *11*(3). https://doi.org/10.29604/BGYY.201209.0008

王进祥. (2013). 奢侈税实施二年之缺失与建言. *土地问题研究季刊*, *12*(4), 28–35.

方钰蓁. (2025). 台积电于高雄科学园区设厂对周遭房价的影响 (未出版硕士論文). 国立暨南国际大学国际企业学系. 台湾博硕士论文知识加值系统. https://hdl.handle.net/11296/52t4wb

刘泰仪, 周南山, & 陈柏翰. (2020). 新型冠状病毒（COVID-19）对台湾营造产业影响之初探. *土木水利*, *47*(1). https://doi.org/10.6653/MoCICHE.202002_47(1).0005

纪博栋. (2019). 中美贸易摩擦下两岸经贸交流数据变化趋势之分析. *中国地方自治*, *72*(11). https://doi.org/10.6581/lsgc.201911_72(11).0002

连文荣. (1998). 亚洲金融风暴对我国出口冲击之评估. *经济前瞻*, (58). https://doi.org/10.30071/EOB.199807.0010

汪瑞芝, 陈明进, & 林世铭. (2005). 土地增值税减半政策之事件研究. *证券市场发展季刊*, *17*(1), 79–104. https://doi.org/10.6529/RSFM.2005.17(1).3

张芷 & 林健生. (2021). 打房再升级！房地合一税 2.0 新制完全解析. *会计研究月刊*, (426). https://doi.org/10.6650/ARM.202105_(426).0006

经济日报. (2026, January 26). *房仲：2025 年全台买卖移转量 26.1 万栋 史上第 3 低 | 房市话题 | 房市*. 经济日报. https://money.udn.com/money/story/5621/9289813

徐世勋, 张静贞, 杨子江, 李笃华, & 林幸君. (2007). 台湾 SARS 疫情经济影响的事后分析. *台湾经济预测与政策*, *38*(1). https://doi.org/10.29629/TEFP.200710.0001

徐俊贤 & 庄荞安. (2015). 房地合一税之解析与因应. *会计研究月刊*, (357). https://doi.org/10.6650/ARM.2015.357.102

谢正一 & 吴毓星. (2010). 探讨 ECFA 对台湾未来发展之影响. *华人经济研究*, *8*(2). https://doi.org/10.30065/JCER.201009.0004

赖裕富. (2018). 海外房地产投资关键因素之研究- 以泰国为例 (未出版硕士論文). 逢甲大学专案管理硕士在职学位学程. 台湾博硕士论文知识加值系统.

SHAPING A SUSTAINABLE SMART FUTURE: A STRATEGIC READINESS ASSESSMENT FOR SCALING UP COMMUNITY-BASED RDF INNOVATIONS IN THE BCG ECONOMY

Narathip Pibanchommee[1*], Chavalit Ratanatamskul[2], and Achara Chandrachai[3]

[1]Technology Management and Innopreneurship Program, College of Interdisciplinary and Integrative Studies, Chulalongkorn University, Bangkok, Thailand
[2]Department of Environmental and Sustainable Engineering, Chulalongkorn University, Bangkok, Thailand
[3]Faculty of Commerce and Accountancy, Chulalongkorn University, Bangkok, Thailand
[*]**Corresponding Author, E-mail:** 6681019820@student.chula.ac.th

Abstract

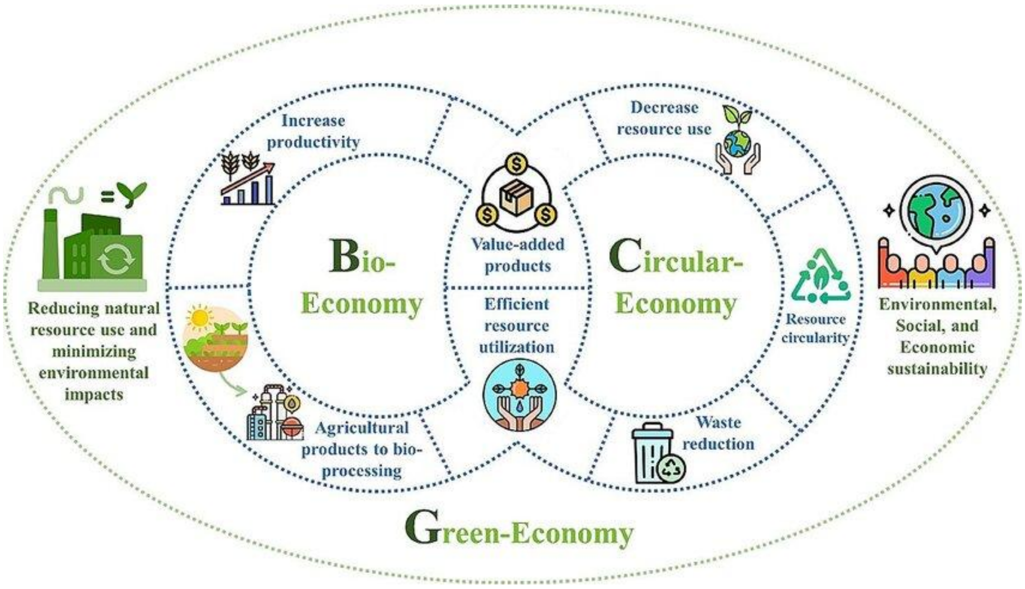
As the global community transitions towards a "Sustainable Smart Future," the integration of circular economy principles and digital innovation has become imperative for effective resource management. This research investigates the strategic readiness for scaling up community-based waste sorting facilities into high-quality Refuse-Derived Fuel (RDF) production units within the framework of Thailand's Bio-Circular-Green (BCG) Economy. Despite the significant potential of community-led initiatives in reducing municipal solid waste, a substantial gap exists between current grassroots sorting capabilities and the stringent technical requirements of industrial-grade RDF. To address this challenge, the study employs a systematic qualitative assessment to develop a multi-dimensional "Readiness Scorecard" evaluating four critical domains: Technical Capability, Management Efficiency, Social Empowerment, and ESG Compliance. The focus is specifically placed on the transition from RDF-3 (Fluff) to RDF-5 (Briquettes), which offers superior energy density and logistics efficiency for industrial applications. By identifying key success factors and operational bottlenecks, the proposed framework serves as a foundational roadmap for local authorities to optimize their infrastructure before integrating advanced AI-driven sorting technologies and smart quality control systems. The findings demonstrate that enhancing management readiness and technical literacy at the community level is essential for achieving excellence in the waste-to-energy supply chain. Ultimately, this research bridges the gap between grassroots waste management and the high-performance excellence required for a digital-ready energy transition, ensuring a sustainable future through economic value creation and measurable greenhouse gas reduction for both local communities and the industrial sector.

Keywords: Sustainable Smart Future, RDF Production, BCG Economy, Readiness Assessment, Waste-to-Energy, Circular Economy

Introduction

In the third decade of the 21st century, the global community is navigating a transformative era defined by the imperative to balance rapid industrialization with environmental preservation. As climate change accelerates, achieving Carbon Neutrality by 2050 and Net Zero Emissions by 2065 has become a core strategic objective for nations worldwide. This global transition has catalyzed the emergence of the "Sustainable Smart Future" paradigm a conceptual framework that integrates high-level technological innovation with the principles of the Circular Economy. Central to this paradigm is the transformation of waste from an environmental burden into a high-value energy resource, facilitated by digital intelligence and advanced manufacturing processes.

In Thailand, the management of Municipal Solid Waste (MSW) has reached a critical juncture. According to the Thailand State of Pollution Report (2024) by the Pollution Control Department, waste generation has surged to approximately 26.95 million tons per annum. While national policies, particularly the Bio-Circular-Green (BCG) Economy model, advocate for Waste-to-Energy (WTE) as a primary solution, the practical implementation remains hindered by systemic inefficiencies. Refuse-Derived Fuel (RDF) represents a vital link in this energy transition, offering a sustainable alternative to fossil fuels in heavy industries. However, a significant quality gap persists in the WTE supply chain, specifically concerning the output from community-based waste sorting facilities.



Picture 1: The integration of RDF production within Thailand's Bio-Circular-Green (BCG) Economy framework.

Source: Adapted from the Department of Climate Change and Environment (2025).

The technical challenges associated with community-led RDF production are multifaceted. Currently, most decentralized facilities produce RDF-3 (Fluff), which is characterized by high moisture content and inconsistent calorific values due to the heterogeneous nature of Thai MSW (Banjerdkit & Suttibak, 2024). While RDF-3 serves as a functional feedstock for certain localized applications, it lacks the energy density and physical stability required for long-distance logistics and large-scale industrial utilization. The transition to RDF-5 (Briquettes)—densified fuel with standardized energy properties—is therefore essential for economic viability and industrial acceptance. This transition, however, requires a level of precision and operational excellence that many community facilities are currently unequipped to provide (Zhu, 2014; Zaman et al., 2024).

The integration of Artificial Intelligence (AI) and Smart Sorting technologies offers a promising pathway to bridge this quality gap. Advanced systems utilizing computer vision and machine learning can optimize the sorting process, ensuring that the raw material for RDF-5 Briquettes is of the highest possible purity (He et al., 2021). Nevertheless, the successful deployment of these "Smart" solutions is contingent upon a baseline of "Strategic Readiness" within the community infrastructure. Without a comprehensive assessment of technical, managerial, and social readiness, the investment in high-tech sorting may fail to yield the expected environmental and economic returns.

Consequently, this research proposes a multidimensional Strategic Readiness Assessment framework. By identifying operational bottlenecks and success factors in the production of RDF-5 Briquettes, this study provides a foundational roadmap for local authorities and stakeholders. This framework does not merely focus on technical throughput but emphasizes the alignment of grassroots innovation with global Environmental, Social, and Governance (ESG) standards and the Thailand Taxonomy (Bank of Thailand, 2024). Ultimately, this research contributes to the "Sustainable Smart Future" by demonstrating how community-based innovations can be scaled through strategic management and digital integration, turning localized waste challenges into national energy opportunities.

Research Objective (s)

1. To evaluate the multi-dimensional readiness levels of community-based facilities in transitioning from RDF-3 (Fluff) to industrial-grade RDF-5 (Briquettes).
2. To identify critical success factors and operational bottlenecks for scaling community RDF innovations under the BCG model and ESG standards.
3. To develop a Strategic Readiness Scorecard as a roadmap for integrating AI and smart technologies into the RDF production supply chain.

Literature Review

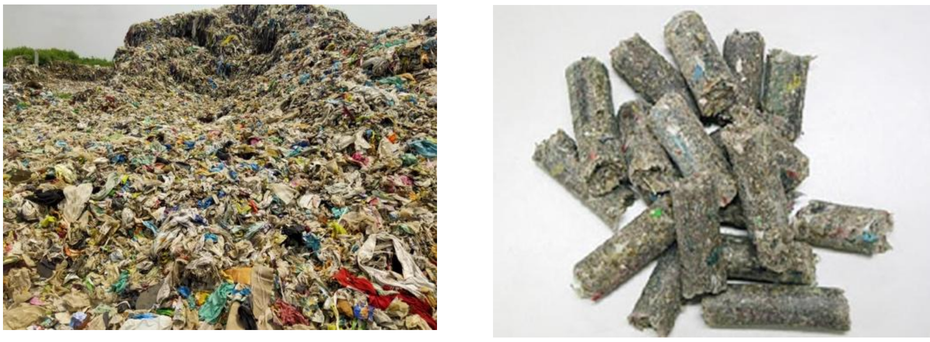
To establish a comprehensive framework for a "Sustainable Smart Future," this research synthesizes multidisciplinary literature covering digital transformation, waste-to-energy (WTE) engineering, and strategic management. The following sections detail the theoretical foundations and current global trends essential for scaling community-based RDF innovations.

1. Sustainable Smart Future and Digitalized Waste Management

In the era of rapid urbanization, the Global Waste Management Outlook 2024 emphasizes that municipal solid waste management must transition from traditional disposal to data-driven circularity. This paradigm shift is a cornerstone of the "Sustainable Smart Future," where digital intelligence enables real-time monitoring of waste streams. According to He et al. (2021), Artificial Intelligence (AI) and CNN-based image recognition have revolutionized sorting efficiency, allowing for the precise identification of recyclables. Furthermore, Mesta (2024) highlights that the integration of robotics and AI-driven sorting is not merely a technical upgrade but a necessity for achieving high-purity feedstock in waste-to-energy supply chains.

2. RDF Standards and Technical Characteristics: RDF-3 vs. RDF-5

The classification of Refuse-Derived Fuel (RDF) has evolved with the introduction of ISO 21640:2021, which replaces older coal-centric standards to provide specific benchmarks for solid recovered fuels.



Picture 2: Physical Transformation from RDF-3 (Fluff) to RDF-5 (Briquettes).

Source: Adapted from International Standards ISO 21640:2021.

2.1. RDF-3 (Fluff): Research by Sumethchotimetha and Sompornpailin (2025) indicates that fluff RDF often suffers from high moisture absorption and low energy density, making long-distance logistics economically challenging.

2.2. RDF-5 (Briquettes): In contrast, densification into briquettes significantly enhances bulk density and storage stability. ISO 21640:2021 categorizes these fuels based on economic value (NCV), technical quality (Chlorine), and environmental impact (Mercury), providing a roadmap for industrial-grade excellence.

Table 1: Detailed Physical and Chemical Characteristics of RDF-3 vs. RDF-5

Parameters	**RDF-3 (Fluff)**	**RDF-5 (Briquettes)**	**Impact on Excellence**
Bulk Density	70–150 kg/m3	450–600 kg/m3	Significantly improves transport efficiency and reduces logistics costs per energy unit.
Heating Value (NCV)	12–15 MJ/kg	18–22 MJ/kg	Enables long-term energy security and industrial compatibility.
Moisture Content	20% – 35%	< 12%	Prevents biological degradation and enhances combustion efficiency.
Storage Stability	Low (Risk of fire/smell)	High (Hydrophobic properties)	Ensures safer long-term storage and stable supply chains.

Source: Adapted from ISO 21640:2021 and Banjerdkit & Suttibak (2024).

As demonstrated in Table 1, the transition from RDF-3 to RDF-5 results in a substantial increase in bulk density, moving from 70–150 kg/m^3 to 450–600 kg/m^3. This physical densification is a critical factor for Logistics Excellence, as it allows for a higher energy-to-volume ratio during transportation. By reducing the volume required for the same energy output, community-based facilities can significantly lower their logistics overheads, making the waste-to-energy supply chain more economically viable within the BCG Economy framework.

แ

Table 2: ISO 21640 Classification Parameters for Solid Recovered Fuels

Classification Parameter	Excellence Metric	Unit
Economic Value	Net Calorific Value (NCV)	MJ/kg (ar)
Technical Quality	Chlorine Content (Cl)	% (d)
Environmental Impact	Mercury Content (Hg)	mg/MJ (ar)

Source: Based on ISO 21640:2021 standards.

3. The BCG Economy and ESG Financing Pathways

Thailand's Bio-Circular-Green (BCG) Economy model serves as the primary policy driver for transforming waste into high-value energy resources. To scale localized innovations, facilities must align with Environmental, Social, and Governance (ESG) standards to attract green financing under the Bank of Thailand (2024) taxonomy framework. The Partnership for Action on Green Economy (PAGE, 2025) suggests that bridging the financing gap for community projects requires transparent data reporting and measurable carbon reduction metrics.

4. Strategic Readiness and Capability Maturity Models

A critical gap identified in existing literature is the lack of specific readiness assessment models for community-scale WTE projects. While traditional Technology Readiness Levels (TRL) focus on technical maturity, Antony et al. (2023) argue that a holistic scoring methodology must include management and organizational readiness. Similarly, Zaman et al. (2024) emphasize that "Community Empowerment" is the foundation of sustainable waste recovery. This research builds upon these principles by developing the T-M-S-E Framework, which integrates the Analytic Hierarchy Process (AHP) as proposed by Saaty (1980) to provide a mathematically rigorous weighting of readiness indicators.

Research Methodology

To achieve the objective of "Shaping a Sustainable Smart Future," this research utilizes a Systematic Qualitative Research Design with a focus on Innovation Management and Strategic Readiness. The methodology is designed to bridge the gap between grassroots waste sorting and industrial-scale energy production. The research process is divided into four distinct phases to ensure a comprehensive evaluation of the "Smart Readiness" of community-based facilities.

1. **Phase 1: Documentary Research and Technical Synthesis**

The initial phase involves a systematic review of international and national technical standards for Refuse-Derived Fuel (RDF). This study synthesizes requirements from ASTM E850, ISO 21640, and EN 15359 to define the technical baseline for RDF-5 (Briquettes). Furthermore, the Bank of Thailand (2024) and the BCG Economy Roadmap (2025) are analyzed to align the readiness criteria with national green financing and environmental targets. This phase establishes the theoretical parameters for "Excellence" in the waste-to-energy supply chain.

2. **Phase 2: Development of the T-M-S-E Readiness Framework.**

The core of this methodology is the development of a multi-dimensional assessment model, categorized into four pillars known as the T-M-S-E Framework. Each pillar represents a critical success factor for scaling community-based innovations

2.1. Technical Readiness (T): Evaluates the physical infrastructure, the efficiency of briquette presses, and the "Digital-Ready" status of the facility (e.g., capability to install AI-based sensors for moisture and calorific monitoring).

2.2. Management Readiness (M): Analyzes the organizational structure, supply chain stability for feedstock collection, and the economic viability of the briquette production model.

2.3. Social Readiness (S): Measures community empowerment, local participation levels, and the digital literacy of community operators (Zaman et al., 2024).

2.4. ESG Compliance (E): Identifies indicators for environmental impact (GHG reduction potential), social equity, and data governance.

3. **Phase 3: Data Collection and Validation**

The research utilizes triangulation of data sources to ensure validity

3.1. Secondary Data: Analyzing operational reports from pilot community waste sorting facilities.

3.2. Field Observations: Conducting site visits to assess the physical workflow from waste reception to the briquetting stage.

3.3. Expert Consultations: Semi-structured interviews with five experts in the fields of Waste-to-Energy, AI/Smart Systems, and BCG Policy to validate the weight of each indicator in the Readiness Scorecard.

The five experts involved in the validation of the Readiness Scorecard were selected through Purposive Sampling based on the following criteria: 1. At least 10 years of professional experience in Waste-to-Energy Engineering or Environmental Management. 2. Demonstrated expertise in Artificial Intelligence (AI) or Digital Transformation within the industrial sector. 3. Active involvement in BCG Economy policy implementation or academic research at a senior level. This ensures that the importance weights assigned to each indicator are grounded in both technical feasibility and national policy alignment.

To ensure objective and scientifically rigorous weighting of the T-M-S-E indicators, this study employed the Analytic Hierarchy Process (AHP), a multi-criteria decision-making framework developed by Saaty (1980). During the expert consultations, the five purposively selected experts performed Pairwise Comparisons of the four pillars and their respective sub-indicators using a 1–9 fundamental scale. The individual comparison matrices were aggregated using the Geometric Mean method to reflect a group consensus. The validity of the expert judgments was confirmed through a Consistency Check, ensuring that the Consistency Ratio (CR) for all matrices remained below the 0.10 threshold, indicating that the derived weights are logically consistent and reliable for the readiness assessment

4. **Phase 4: Data Analysis and Strategic Projection**

The collected data is analyzed using **Content Analysis** and **Benchmarking**. The readiness of the community innovation is mapped against the industrial requirements for RDF-5. The study uses **Strategic Projection** to estimate the greenhouse gas (GHG) reduction impact if the facility reaches the highest readiness level. The final output is the **"RDF Readiness Scorecard,"** designed as a decision-support tool for "Shaping a Sustainable Smart Future."

Results

The results of this study involve the systematic development of a strategic evaluation instrument designed to measure the scalability of community-based waste innovations. The findings are presented through the development of the T-M-S-E Readiness Framework and the categorization of maturity levels for RDF production.

1. The T-M-S-E Strategic Evaluation Instrument

The primary result is the establishment of a "Readiness Scorecard" derived from a synthesis of global waste-to-energy standards. The scorecard categorizes indicators into four pillars: Technical (T), Management (M), Social (S), and ESG Compliance (E). This instrument allows local authorities to pinpoint specific operational gaps before investing in advanced technologies.

The Importance Weights presented in Table 2 were systematically derived from the AHP synthesis of expert judgments. The Technical (T) and Management (M) pillars emerged as the most critical dimensions, each carrying a 35% cumulative weight (distributed across sub-indicators), reflecting their foundational role in achieving operational excellence in RDF-5 production. The Social (S) and ESG (E) pillars provide the necessary framework for long-term sustainability and digital integration, contributing the remaining 30% of the total readiness score. This weighted structure allows local authorities to prioritize interventions that yield the highest impact on energy transition readiness.

Table 3: Detailed Performance Indicators and Definitions of the T-M-S-E Readiness Scorecard

Dimension	Indicator Code	Definition and Assessment Metric	Importance Weight
Technical (T)	RD-T1	Briquette Quality Excellence: Measures mechanical pressure stability and the physical density of the final RDF-5 product.	20%
	RD-T2	Pre-processing Precision: Evaluates the efficiency of moisture reduction	15%

		and shredding consistency to ensure feedstock purity.	
Management (M)	RD-M1	Supply Chain Resilience: Assesses the stability and digitalization of the municipal waste collection and logistics system.	20%
	RD-M2	Economic Circularity: Measures the transparency of financial auditing and the efficiency of the revenue-sharing model.	10%
Social (S)	RD-S1	Community Sorting Compliance: Evaluates the level of resident participation and accuracy in at-source waste segregation.	10%
	RD-S2	Digital & Technical Literacy: Measures the ability of local operators to manage and interpret data from smart monitoring systems.	10%
ESG (E)	RD-E1	Net-Zero Accountability: Tracks the capacity for real-time greenhouse gas (GHG) monitoring and carbon credit reporting.	15%

Source: Developed by the author based on the T-M-S-E Framework (2026).

Table 4: Comparison of Densification Technologies for Community-Scale RDF

Technology	**Pressure Level**	**Suitability for Thai MSW**	**Smart-Ready Potential**
Screw Press	Moderate	Best for high-fiber moist waste	High (Easy sensor integration)
Piston Press	High	Good for low-moisture waste	Moderate
Pellet Mill	Very High	Requires pre-drying/Uniformity	Low for community-scale

Source: Synthesized from (Global Infrastructure Basel, 2024) and Owoade & Adebola (2025).

2. Maturity Level Categorization (Level 1 to Level 5)

The research identified five distinct maturity levels for community-based facilities. The results indicate that most grassroots initiatives currently operate at Level 2 or 3, where they can produce RDF-3 (Fluff) but lack the precision to stabilize quality for RDF-5 (Briquettes).

Table 5: Maturity Evolution Model for Community-Based RDF Production Excellence

Maturity Level	**Stage Name**	Primary Characteristics & Infrastructure	RDF Output Capacity	Smart/ AI Readiness Status
Level 1	Initial	Raw waste collection with minimal manual sorting.	Low- quality mixed waste (Unprocessed).	No digital or mechanical infrastructure.
Level 2	Organized	Structured manual sorting; basic separation of combustibles and non-combustibles.	Raw feedstock for RDF-3.	Manual data recording for waste volume.
Level 3	Developing	Use of mechanical shredding and basic briquetting systems; however, calorific values remain inconsistent.	RDF-3 (Fluff) and low-grade RDF-5.	Basic power monitoring; no real-time quality sensors.
Level 4	Advanced	Systematic production of high- density briquettes; established supply chain stability.	Industrial-grade RDF-5 (Briquettes).	Capable of hosting AI-based sensor integration.
Level 5	Smart-Ready	Fully integrated systems with AI-ready sensor interfaces for real- time quality monitoring.	High- performance RDF-5 with guaranteed specs.	Full AI-driven sorting and predictive quality analytics.

Source: Synthesized from the T-M-S-E Readiness Framework and RDF-5 industrial standards.

The maturity levels presented in Table 4 illustrate that the transition from a grassroots sorting facility to an industrial-grade energy producer is a non-linear evolution. While most community facilities in the Thai context currently operate at Level 1 or Level 2, achieving Level 3 (Developing) is a critical milestone as it marks the beginning of mechanical densification into RDF-3. However, the ultimate goal for a Sustainable Smart Future is reaching Level 5 (Smart-Ready), where AI-driven sorting optimizes the purity of the raw materials. This integration ensures that the final RDF-5 Briquettes meet the stringent calorific and moisture standards required by large-scale industries, effectively bridging the gap between community efforts and industrial excellence.

3. Empirical Application: A Case Study of Community A

To demonstrate the practical application of the T-M-S-E Readiness Scorecard, a representative case study of a suburban community facility (referred to as 'Community A') was conducted. The assessment is based on a synthesis of secondary operational data and expert-validated scenarios to illustrate how the scorecard identifies critical gaps in the waste-to-energy supply chain.

3.1 Weighting Derivation via AHP Method

In response to reviewer recommendations, the importance weights for each indicator were derived using the Analytic Hierarchy Process (AHP). The five experts consulted in Phase 3 performed pairwise comparisons of the four pillars. The resulting Consistency Ratio (CR) was 0.04, which is well within the acceptable threshold of 0.10, ensuring the mathematical validity of the weights assigned to the scorecard.

Table 6: Readiness Assessment Results for Community A

Dimension	**Indicator**	**Weight (W)**	**Actual Score (S) (1-5)**	**Weighted Score (W×S)**
Technical (T)	RD- T1: Briquette Quality	20%	3	0.60
	RD-T2: Pre-processing	15%	3	0.45
Management (M)	RD-M1: Supply Chain	20%	4	0.80
	RD- M2: Economic Circularity	10%	3	0.30
Social (S)	RD- S1: Community Sorting	10%	5	0.50
	RD-S2: Digital Literacy	10%	2	0.20
ESG (E)	RD- E1: Net- Zero Tracking	15%	2	0.30
Total Readiness Score		**100%**		**3.15**

3.2 Analysis of ResultsThe Community A achieved an overall readiness score of 3.15, placing it firmly at Maturity Level 3 (Developing). Strengths: The facility shows exceptional Social Readiness (RD-S1 = 5), indicating high resident compliance in waste segregation at the source. Management efficiency is also robust due to a stable municipal collection system (RD-M1 = 4). Critical Gaps: The primary bottlenecks are Digital Literacy (RD-S2 = 2) and ESG Accountability (RD-E1 = 2). While the facility can physically produce RDF-3, the operators lack the technical training to manage smart monitoring interfaces required for RDF-5 Excellence. Strategic Projection: By investing in digital literacy training and IoT-based moisture sensors, the facility could theoretically increase its score to 4.20 within twelve months, transitioning to Level 4 (Advanced) and becoming "AI-Ready".

The data presented in this case study is based on a Pilot Assessment of a representative community facility, validated through expert consultations to demonstrate the practical utility of the T-M-S-E Scorecard.

Discussion

The discussion interprets the results through the lens of the Sustainable Smart Future theme, focusing on how strategic readiness acts as a catalyst for technological excellence.

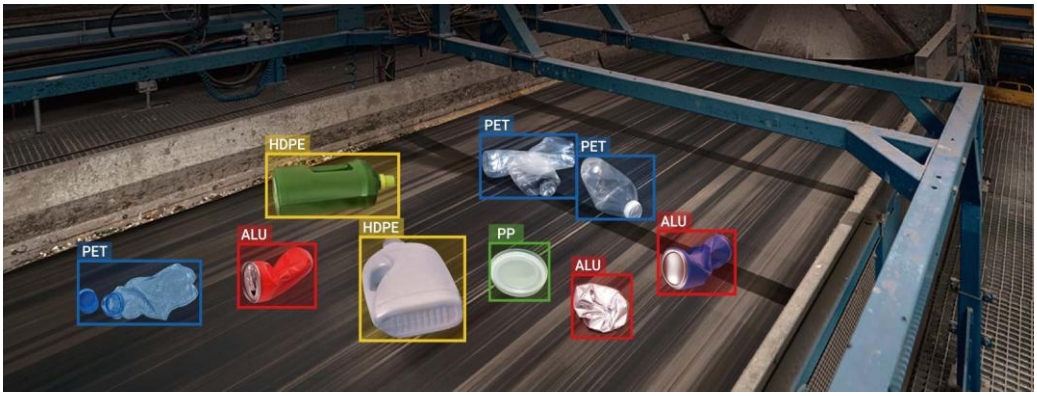
1. Bridging the Quality Gap: From RDF-3 to RDF-5 Excellence

The transition from RDF-3 (Fluff) to RDF-5 (Briquettes) is more than a physical change; it is a shift toward industrial excellence. As established in the literature (ISO 21640:2021; Banjerdkit & Suttibak, 2024), Fluff RDF is highly susceptible to moisture re-absorption, which degrades its heating value during transport. The results of the T-M-S-E assessment suggest that technical readiness in moisture control is the highest barrier for Thai communities. By densifying waste into Briquettes, communities can achieve "Logistics Excellence," reducing transportation costs per unit of energy and making the BCG model economically viable.

2. The Role of Digital Intelligence (AI) in Shaping a Smart Future

In alignment with the conference theme of "Integrating AI for Excellence," this study argues that AI should not be viewed as a standalone solution but as a "Readiness Multiplier." The Technical (T) indicators in the results show that for AI-driven sorting to be effective, a facility must first reach a Level 4 maturity. Advanced computer vision systems (He et al., 2021) can be integrated into the briquetting line to ensure that only high-purity materials are compressed. This digital intervention ensures that the final RDF-5 Briquettes meet the stringent standards of heavy industries, such as cement manufacturing and large-scale power plants.

As illustrated in Picture 3, the conceptual interface demonstrates how AI monitors moisture and quality a critical insight from the Technical (T) and Social (S) readiness scores is that AI integration is not merely a financial investment but a cultural and technical shift. For AI-driven computer vision systems to achieve operational excellence, community operators must possess the 'Digital Literacy' (RD-S2) to calibrate sensors and respond to data anomalies in real-time. Therefore, the 'Strategic Readiness Scorecard' serves as a prerequisite diagnostic tool, ensuring that AI becomes a 'Readiness Multiplier' rather than an underutilized high-tech asset.



Picture 3: Conceptual Smart Monitoring Interface for RDF-5 Quality Excellence.

Source: Adapted from the digital intelligence framework for a Sustainable Smart Future.

3. Scaling Innovations through ESG and Social Empowerment

A critical finding in the Social (S) and ESG (E) pillars is that community empowerment is the foundation of data accuracy. For a "Smart Future" to be sustainable, the data regarding waste volumes and carbon reduction must be transparent. The discussion emphasizes that higher "Digital Literacy" among community operators (Zaman et al., 2024) leads to better data governance, which in turn allows the facility to access green financing under the Bank of Thailand (2024) framework. This creates a virtuous cycle where social readiness fuels technical and economic excellence.

4. Strategic Roadmap for Local Authorities

Finally, the RDF Readiness Scorecard provides a clear roadmap for policy implementation. Instead of broad-spectrum technology subsidies, the government should focus on "targeted readiness interventions." For instance, facilities scoring low on Management (M) should receive business training before being awarded grants for AI-driven machinery. This strategic approach ensures that the scaling up of community innovations is both efficient and future-proof.

Conclusion

This research has established a strategic framework for scaling up community-based waste sorting innovations into high-quality RDF-5 Briquette production units. By addressing the critical gap between grassroots waste management and industrial energy requirements, this study provides a foundational roadmap for achieving operational excellence within the BCG Economy.

1. Summary of Findings

The development of the T-M-S-E (Technical, Management, Social, and ESG) Readiness Framework serves as the primary contribution of this study. The research concludes that the transition from RDF-3 (Fluff) to RDF-5 (Briquettes) is not merely a mechanical upgrade but a systemic transformation. The results from the Readiness Scorecard indicate that while community participation (Social Readiness) is often high in Thai contexts, the primary barriers to scaling are technical precision in moisture control and digital literacy. For community facilities to achieve industrial-grade output, they must move beyond basic sorting toward a "Smart-Ready" status (Level 5), characterized by the integration of data-driven quality control.

2. Shaping a Sustainable Smart Future

In alignment with the goal of "Integrating AI for Excellence," this research concludes that digital intelligence acts as a catalyst for sustainability. The application of AI-driven sorting and smart monitoring systems ensures that RDF-5 Briquettes meet the stringent calorific and chemical standards required by heavy industries. However, a key insight of this study is that technological investment must be preceded by strategic readiness. AI integration is most effective when the management and social pillars are robustly developed, ensuring that the technology is supported by accurate data and a skilled local workforce.

3. Policy and Practical Implications

For local authorities and policymakers, the RDF Readiness Scorecard offers a diagnostic tool to optimize resource allocation. Rather than universal subsidies for machinery, the findings suggest a "Targeted Intervention" approach—focusing on bridging the specific gaps identified in the T-M-S-E assessment. Furthermore, by aligning community outputs with ESG standards and the Bank of Thailand, these facilities can unlock green financing opportunities, ensuring long-term economic circularity and contributing significantly to Thailand's Net Zero Emissions targets.

4. Recommendations for Future Research

Future studies should focus on the empirical validation of the scorecard through long-term pilot implementations in diverse geographic regions of Thailand. Additionally, research into the development of low-cost, AI-enabled moisture and calorific sensors specifically designed for community-scale briquette presses would further accelerate the transition toward a digitalized and sustainable energy future.

References

Antony, J., Sony, M., & Gutierrez, L. (2023). A scoring methodology for Industry 4.0 maturity assessment. Journal of Manufacturing Technology Management. https://doi.org/10.1108/jmtm-11-2024-0635

Bank of Thailand. (2024). *Thailand taxonomy phase 1: Waste management sector.* https://www.bot.or.th/en/financial-innovation/sustainable-finance/green/Thailand-Taxonomy.html

Banjerdkit, P., & Suttibak, S. (2024). Environmental and climate impacts associated with Refuse Derived Fuel (RDF) production: A case study in Thailand. *E3S Web of Conferences*, *516*, 04006. https://doi.org/10.1051/e3sconf/202456604006

Department of Climate Change and Environment. (2025). *BCG economy action plan for carbon neutrality.* Ministry of Natural Resources and Environment. https://www.bcg.in.th/eng/wp-content/uploads/2022/07/BCG_Action_Plan_-Eng_Small.pdf

Global Infrastructure Basel. (2024). *Sustainability and readiness assessment framework for waste-to-energy projects in emerging economies*. GIB Foundation.

He, X., Zhang, Y., & Liu, J. (2021). Artificial intelligence in waste sorting: Advancing recycling processes through CNN-based image recognition. *Journal of Environmental Management*, *289*, 112522. https://doi.org/10.1016/j.jenvman.2021.112522

International Organization for Standardization. (2021). *Solid recovered fuels-Specifications and classes.* https://cdn.standards.iteh.ai/samples/71309/83d2593faf44431faf9276f20aa30eff/ISO-21640-2021.pdf

Mesta, D. (2024). AI and robotics in waste sorting: Enhancing recycling efficiency. *Advances in Recycling & Waste Management*, *9*(4). https://www.hilarispublisher.com/open-access/ai-and-robotics-in-waste-sorting-enhancing-recycling-efficiency.pdf

Owoade, R., & Adebola, A. (2025). Community-based waste management strategies and their impact on urban sustainability through citizen participation. *World Journal of Advanced Research and Reviews*, *15*(2), 214–230

Partnership for Action on Green Economy. (2025). *Thailand takes a step toward circularity: Financing pathways for sustainable waste management.* United Nations Environment Programme. https://www.un-page.org/news/thailand-takes-a-step-toward-circularity/

Pollution Control Department. (2024). *Thailand state of pollution report 2023.* Ministry of Natural Resources and Environment.

Saaty, T. L. (1980). *The analytic hierarchy process: Planning, priority setting, resource allocation*. McGraw-Hill.

Sumethchotimetha, R., & Sompornpailin, K. (2025). *Sustainable Waste Management Improves the Quality of Industrial RDF Production and Benefits the Environments.* Current Applied Science and Technology, e0265123. https://doi.org/10.55003/cast.2025.265123

United Nations Environment Programme. (2024). *Global waste management outlook 2024: Beyond an age of waste.* https://www.unep.org/resources/global-waste-management-outlook-2024

Zaman, B., Sumiyati, S., Wati, H. R., & Aisy, A. R. (2024). Recovery of solid waste as refuse derived fuel (RDF) to develop urban waste management through community empowerment. *IOP Conference Series: Earth and Environmental Science*, *1414*(1), 012021. https://doi.org/10.1088/1755-1315/1414/1/012021

数实融合对制造企业绿色创新绩效的影响研究——基于知识治理的视角

THE IMPACT OF INTEGRATION OF DIGITAL AND REAL ECONOMIES ON GREEN INNOVATION PERFORMANCE OF MANUFACTURING ENTERPRISES—A PERSPECTIVE OF KNOWLEDGE GOVERNANCE

廖睿文*
Ruiwen Liao*

泰国正大管理大学泰华国际学院，中国广西财经学院
International Chinese College, Panyapiwat Institute of Management, Thailand
Guangxi University of Finance and Economics, China
***Corresponding Author, E-mail:** lrw@gxufe.edu.cn

摘要

数实融合已成为制造业高质量发展的关键动能，在全球环境问题日益严峻，中国高质量发展亟需多方发力的背景下，探索数实融合如何影响绿色创新，通过何种机制赋能绿色创新，具有重要理论与实践意义。在对中国 6 个省份制造企业管理者的 366 份问卷调查的基础上，结合回归分析和中介效应模型，本文对数实融合影响制造企业绿色创新绩效的效应进行了考察，核心发现如下：数实融合对制造企业绿色创新绩效具有显著正向影响，数实融合已成为驱动制造企业绿色创新发展的重要动力；知识治理在数实融合与制造企业绿色创新绩效之间发挥中介作用。本文为理解数实融合的绿色赋能效应提供了理论与实证支撑，同时为制造企业绿色转型及政策制定提供了实践参考。

关键词： 数实融合 制造企业 知识治理 中介效应 绿色创新绩效

Abstract

The integration of the digital and real economies has become a key driver for the high-quality development of the manufacturing industry. Against the backdrop of increasingly severe global environmental issues and China’s urgent need for multi-faceted efforts towards high-quality development, exploring how digital-real integration affects green innovation and the mechanisms through which it enables green innovation holds significant theoretical and practical importance. Based on a survey of 366 manufacturing enterprise managers from six provinces in China, combined with regression analysis and a mediation effect model, this paper examines the impact of digital-real integration on the green innovation performance of manufacturing enterprises. The main findings are as follows: First, digital-real integration has a significant positive impact on the green innovation performance of manufacturing enterprises, establishing itself as an important driving force for their green innovation development. Second, knowledge governance plays a mediating role in the relationship between digital-real integration and the green innovation performance of manufacturing enterprises. This paper provides theoretical and empirical support for understanding the green enabling effects of digital-real integration, while also offering practical insights for the green transformation of manufacturing enterprises and relevant policy formulation.

Keywords: Digital-Real Integration, Manufacturing Enterprises, Knowledge Governance, Mediating Effect, Green Innovation Performance

引言

数字经济时代，数字技术与实体企业的融合（以下简称数实融合）已成为推动制造业转型升级的关键力量。数实融合是将数字技术应用在实体经济中，形成数字经济和实体经济之间相互作用和良性循环的过程，通过持续提升社会经济的数字化、网络化和智能化程度，形成的一种新型经济模式。随着大数据、人工智能等技术的迅猛发展，数字技术正逐步渗透到制造业的各个环节，从产品设计、生产流程、供应链管理、企业管理都发生了深刻的变革。数实融合不仅提升了制造业的生产效率和产品质量，更为制造企业的绿色创新提供了新的动力和可能。

与此同时，面对全球气候变化和资源环境约束的严峻挑战，在“双碳目标”的约束下，有效实施绿色创新战略是促进要素有序流动、资源高效配置、缓解环境压力、推动产业绿色发展与转型升级的重要内容与关键突破口（吴建祖 & 马晴，2025），作为一种既能实现产品价值提升又能减少对环境负面影响的企业活动（解学梅 & 朱琪玮，2021）。绿色创新已成为制造企业实现高质量发展的重要抓手（揭筱纹 & 宁胜男，2021），为经济可持续发展提供了不可或缺的技术支撑（Sun et al., 2023）。制造企业作为中国构建市场化绿色创新体系的重要主体，应将当前的数字技术融入可持续发展。然而，绿色创新需要高昂的研发投入和长期的技术积累，对于许多制造企业而言是一大挑战，数实融合为改变这种挑战提供了可能。在这一背景下，研究数实融合如何影响制造企业的绿色创新绩效，对于把握制造业转型升级的新趋势、发力推动制造业高质量发展具有重要意义，也符合新时代对数实融合“赋能”理论和实践深化的需要。

事实上，近年来学者们对于数实融合的影响效应进行了卓有成效的探讨，主要涉及数实融合对经济增长、产业转型与绿色创新的影响。然而，在微观企业层面，现有研究对数实融合与制造企业绿色创新之间的探讨还有待拓展和完善。与此同时，在数实融合向制造企业绿色创新渗透的过程中，数字技术的赋能并非自动实现，其价值转化需依托对知识这一核心生产要素的有效管理。越来越多的经验研究证实，数实融合并非天然地、线性地转化为绿色创新绩效，而是高度依赖企业对数字知识、绿色知识进行治理的能力（宋华等，2023；徐建中，2017）。理论逻辑看，数实融合对绿色创新绩效的影响需经历“技术赋能-知识转化-创新落地”的传导过程，而知识治理正是衔接这一过程的核心机制。知识治理被认为是采用一定的组织机构、协调机制进行知识的交流、共享和创新（Grandori，2001；Gooderham，2011）。在数实融合日益深化的背景下，制造企业能否将数字资源与物理要素有效转化为绿色创新动能，关键取决于其对知识资源的治理能力。然而现有研究对于知识治理在数实融合与绿色创新关系中的作用关注不足。

与现有研究相比，本文创新之处在于：一方面，本文从微观企业角度拓展了数实融合赋能绿色创新的研究视角，是对绿色创新驱动因素的理论拓展。进一步地，已有研究鲜有关注知识治理在数实融合与绿色创新之间的中介传导作用。本文基于知识治理这一中介变量的研究，拓宽了数实融合作用于绿色创新的理论机理的认知边界。另一方面，本文实证揭示了知识治理在数实融合与绿色创新绩效二者之间的中介效应，为后续研究提供了新的变量参考和论据支撑。总之，从数实融合角度看，本文有利于探寻和揭示数实融合的绿色赋能效应，是对于数实融合的赋能效应研究范围的拓展和丰富；从绿色创新角度看，本文为绿色创新的驱动因素提供了新的变量依据、实证依据，丰富了对于：哪些变量影响了绿色创新？这些变量通过什么路径影响的绿色创新？又在多大程度上影响绿色创新？等位于同一逻辑链条的多个问题的回答。

研究目的

本文主要研究目的主要有两个：一方面，探明数实融合对制造企业绿色创新绩效的直接影响效应是什么。通常而言，随着数实融合不断推进，会从多个层面对制造企业产生影响，那么数实融合究竟会对制造企业绿色创新产生什么影响，能否将数实融合视为制造企业绿色创新发展的一个有效驱动力，本文将给予验证。另一方面，如果数实融合能够有效促进制造企业绿色创新，那么企业的知识治理能力，是否能够成为数实融合作用于制造企业绿色创新传导过程中的有效中介？本文第二个研究目的在于探明知识治理传导路径是否存在。

文献综述

与本文密切相关的研究主要集中在如下三个维度，其一，数实融合的经济增长和产业转型的影响；其二，数实融合对绿色创新的影响；其三，知识治理对企业绩效的影响。

数实融合对经济增长和产业转型的影响

目前数实融合对于经济增长影响的研究主要集中于相对宏观视角，并论述数实融合与经济高质量发展之间的关系，揭示数实融合对经济高质量发展的推动作用（张倩等，2024；杨东亮 & 丁晨曦，2024）。学者们普遍认为数实融合不仅有助于保障产业链与供应链的稳定，推动外商直接投资的稳步扩大，还有助于创造更多的工作机会，推动经济发展（邝劲松 & 彭文斌，2020）。从推动产业转型升级看，研究指出数实融合产生“倍增效应”，能够赋能传统产业转型升级（杜金柱 & 扈文秀，2023；石玉堂等，2025）。研究指出数实融合过程中，数据要素能够渗透社会再生产各环节，将传统经营模式转变为数字化经营模式，实现实体经济业务流程优化，从而提高生产要素在产业间的配置效率，推动产业结构升级（周文 & 施炫伶，2023）。

数实融合对绿色创新的影响

从赋能绿色创新看，学界的探讨取得了一定的进展。现有关于数实融合与绿色创新的研究初步揭示了数实融合对绿色创新的促进作用。例如，史丹 & 孙光林（2023）指出，提高数字经济和实体经济融合水平有利于促进绿色创新；崔琳昊 & 冯烽（2024）指出数实融合通过促进产业结构升级和技术进步推动了城市产出扩张、投入优化和治理提升，进而促进了城市绿色发展；研究还指出数实融合有助于提高产品质量，提升生产效率，促进包括绿色技术在内的技术创新，从而推动企业绿色化转型（曹增栋 & 岳中刚，2024）。

知识治理对企业绩效的影响

随着知识经济时代的兴起，知识治理机制对企业的重要性不言而喻。知识作为一种重要的生产要素，逐渐成为企业竞争的核心，企业开始关注如何有效地获取、整合和利用知识，以提升自身的核心竞争力（李佳轩 & 储节旺，2024）。知识治理是组织通过一系列制度建设和治理机制如工作设计、报酬系统等，来影响组织和个体知识活动的过程，其目的是优化组织绩效 Grandori（2001）。研究发现，提高知识治理水平可有效解决“卡脖子”问题，激发创新生态系统向更高阶段演化（许学国等，2025）。近年来，学者们增加了对于隐性知识传播、共享等知识治理的研究，揭示了知识治理广泛性和知识治理深入性在联盟知识治理机制与联盟突破性创新间发挥的中介作用，分析了知识治理机制、知识治理对于突破性创新的作用（施锦诚等，2023；Aslam et al., 2024）。

总的来看，尽管研究者们对于数实融合与经济、产业、绿色创新的研究不断增多，并且关注到了知识治理与企业绩效的关系，但从微观角度论述数实融合与企业绿色创新的关系仍然不足，并且鲜有关注知识治理在数实融合与绿色创新之间的中介效应。

研究假设

1. 数实融合对制造企业绿色创新的直接影响效应

制造企业对数字技术的采用可以从生产、管理、融资等多个层面对自身产生影响，从而对企业绿色创新产生影响。首先，从生产成本层面看，数实融合通过智能化生产、精准化控制等方式，减少资源浪费和能源损耗，提升企业的创新能力和生产效率（张沥幻 & 张金昌，2024）。从管理层面看，数实融合打破企业间的信息壁垒，消除“数据孤岛”现象，数字经济与实体经济的深度融合要求企业重新配置已有的资源，对组织结构和商业模式进行创新，推动实体企业组织管理模式趋于数字化、扁平化、协同化和专业化，有利于降低企业内部管控成本和改善企业运营绩效（朱瑞博，2025；Fitzgerald et al., 2014）。从融资层面看，数实融合有利于降低不同部门间的信息不对称，增强企业的绿色融资能力。以制造企业获取融资为例，数实融合有助于金融机构获取企业的相关信息（史丹 & 孙光林，2023），有利于充分披露企业环境信息。通过更多的信息披露，金融机构更有效地分析企业的真实情况，增强企业绿色信贷的可信度和支持力度。这有利于缓解企业的融资约束，提升制造企业的绿色创新所需要的资金支持。基于以上分析，提出如下待检验假设：

H1：数实融合对制造企业绿色创新绩效产生直接正向影响

2. 知识治理在数实融合与制造企业绿色创新过程中的中介效应

数字经济时代，企业突破了传统组织边界的资源限制，而知识基础的拓展会提高企业创新的成功率。数智时代的知识生产能够融合智能技术和人类主体的知识、经验，可以在内涵上嫁接形成更高层次的价值认知，并开发出具有突破性意义的产品和服务，促进企业创新绩效。已有不少研究表明，有效的知识治理对企业创新绩效提升具有重要作用，产生的新知识可以促进创新绩效增长（Ruiz-Jiménez & Fuentes-Fuentes，2016）。

随着数实融合不断推进，制造企业基于云计算、人工智能等技术不断优化组织管理，企业能够实现对海量数据的收集、分析和挖掘（Goldfarb & Tucker，2019），从而更加准确地识别绿色创新的机遇。数实融合通过推动技术知识以及信息资源的获取、吸收与整合，从而应

对绿色创新周期长、风险大等问题，最终使企业的绿色创新能力得到提升。基于以上分析，提出如下待检验假设：

H2a：数实融合正向影响制造企业知识治理

H2b：知识治理正向影响制造企业绿色创新绩效

H2：知识治理在数实融合与制造企业绿色创新绩效之间起中介作用

综上，为验证以上假设，本文将制造企业绿色创新绩效作为研究的因变量，数实融合作为自变量，知识治理作为中介变量，理论框架模型如图（图 1）。

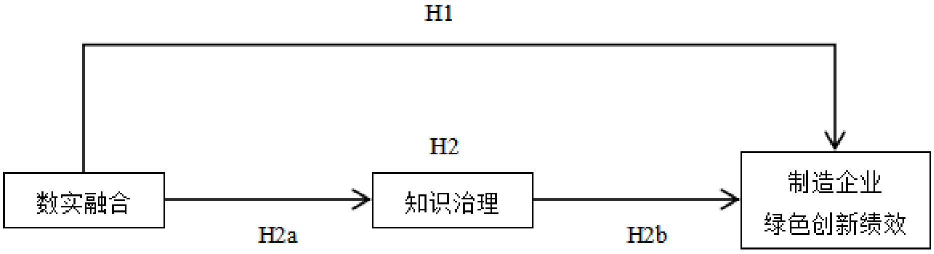


图 1: 理论模型

研究方法

1. 问卷发放

本文采用问卷调查法收集样本数据，调研对象为制造企业的管理者，调查地区主要选择中国山东、广东、湖南、河南、陕西、广西 6 个省份。调查工作开展于 2025 年 4 月至 5 月，主要通过两种渠道收集数据。其一，依托本人所在课题组，在课题组实地园区调研的过程中现场发放问卷，请企业熟悉数实融合过程的中高层管理者进行填写，并通过滚雪球方式采访更多企业管理者。第二，遵循分层抽样方法，委托一家具有丰富经验和良好资质的专业数据采集服务公司发放问卷，通过样本服务，指定问卷发放省份、指定调研对象为中高层管理者、指定所在行业为制造业，进行问卷发放。

通过上述两种途径，本次调查共发放问卷 500 份。经过整理，最终得到有效问卷 366 份，有效问卷率为 73.2%。为保证研究结论的可靠性和合理性，按照 Nunnally 和 Bernstein（1994）的建议，问卷题项数量与有效样本数量的比例应达到 1:5。本文问卷题项数量为 35，样本容量满足要求，可以开展后续数据分析。

2. 样本分布

从行业分布来看，本次调查取样结果来自不同类型的制造业，具体包括电器机械及器材制造业 63 家占 17.2%，食品加工制造业 57 家占 15.6%，通用设备制造业 54 家占 14.8%，电子、计算机及通信设备制造业 44 家占 12.0%，生物、化学及医药制造业 36 家占 9.8%，交通运输设备制造业 34 家占 9.3%，纺织与服装业 21 家占 5.7%，石油加工及炼焦业 18 家占 4.9%，以及其他制造业 39 家占 10.7% 。就企业所在地区而言，欠发达地区省份企业数量供 208 家，占比为 56.8%，发达地区省份企业 158 家， 占比为 43.2%。

3.　量表设计

本文涉及 3 个主要变量，采用基于问卷的量表形式获取相关数据。各变量的题项及相关参考文献概述如下。其一，数实融合。其核心内涵在于，企业利用数字技术赋能核心业务、产品/服务创造、管理和商业模式，最终实现价值创造和效率提升（池毛毛等，2020；周密等，2024），参考《中小企业数字化水平评测指标（2024 年版）》、池毛毛等（2020），本文在对已有题项略微调整的基础上将数实融合的题项梳理为数实融合基础、经营、管理、成效四个维度，共计 13 个题项。其二，知识治理。本文知识治理参考学者（Gooderham et al., 2011；向阳和曹勇，2015；白景坤等，2022），题项包含 3 个维度，共计 12 个题项。其三，企业绿色创新绩效。本文绿色创新绩效量表借鉴胡石其、熊磊（2018）的量表，题项包含 4 个维度，共计 10 个题项。

研究结果

1.　信效度检验及样本描述性统计

1.1　信度检验

表 1 为内部一致性信度检验结果。本研究涉及的数实融合量表的 Cronbach'α 系数为 0.873；知识治理量表的 Cronbach'α 系数为 0.867；绿色创新绩效量表的 Cronbach'α 系数为 0.902，均高于 0.7。另外，校正条目总相关性系数（CITC）也可以用于评估量表的可靠性，当 CITC 大于 0.5 时，说明量表各选项与量表整体构念之间存在较强的内部一致性，具有较高的信度。由表可知，量表中所有题项的 CITC 值在 0.605 到 0.774 之间，均高于 0.5。表明数实融合、知识治理、绿色创新绩效这 3 个变量的数据均具有较高的内部一致性，符合研究的要求。

表 1: 主要变量信度检验结果

变量名称	题项	CITC	删除项后 Cronbach's α 系数	Cronbach's α 系数
数实融合	GRI1	0.712	0.848	0.873
	GRI2	0.678	0.856	
	GRI3	0.715	0.847	
	GRI4	0.725	0.845	
	GRI5	0.729	0.833	
	GRI6	0.727	0.839	
	GRI7	0.667	0.861	
	GRI8	0.712	0.851	
	GRI9	0.647	0.807	
	GRI10	0.728	0.725	
	GRI11	0.734	0.843	
	GRI12	0.681	0.854	
	GRI13	0.699	0.850	

变量名称	**题项**	**CITC**	**删除项后 Cronbach's α 系数**	**Cronbach's α 系数**
知识治理	KG1	0.710	0.849	0.867
	KG2	0.752	0.842	
	KG3	0.717	0.837	
	KG4	0.699	0.843	
	KG5	0.727	0.835	
	KG6	0.674	0.846	
	KG7	0.692	0.842	
	KG8	0.641	0.799	
	KG9	0.721	0.718	
	KG10	0.696	0.739	
	KG11	0.728	0.849	
	KG12	0.695	0.856	
绿色创新绩效	GIP1	0.774	0.884	0.902
	GIP2	0.683	0.892	
	GIP3	0.605	0.898	
	GIP4	0.672	0.893	
	GIP5	0.696	0.891	
	GIP6	0.715	0.889	
	GIP7	0.729	0.888	
	GIP8	0.753	0.886	
	GIP9	0.776	0.871	
	GIP10	0.731	0.857	

接着对变量进行组合信度检验。组合信度 CR 反映了由多个测量指标组合而成的整体对构念测量的一致性和稳定性。当 CR 值大于等于 0.7 时，说明组合信度良好。本文中各变量的组合信度 CR 值汇总如表 2。由表可知数实融合、知识治理、绿色创新绩效的组合信度 CR 值分别为 0.898、0.913、0.927，均大于 0.7，说明各变量测量能有效反映构念特征，符合研究要求。

表 2: 各变量组合信度 CR 值

变量	**数实融合**	**知识治理**	**绿色创新绩效**
组合信度 CR 值	0.898	0.913	0.927

1.2 效度检验

效度分析是检验量表对所测量的对象所能达到的准确程度或有效性，也即对测量对象的行为特征的准确性。本文采用验证性因子分析（CFA）对量表的效度进行检验，结果见表 3。

由表 3 结果可知，绝大多数拟合指标均达到判别标准，仅有拟合优度指数 GFI 值略小于 0.9，但仍大于 0.8，处于可接受的范围内（χ2/df =2.635；比较拟合指数 CFI=0.935；拟合优度指数 GFI=0.854；调整后的拟合优度指数 AGFI=0.902；标准化残差均方根 SRMR=0.044，近似均方根误差 RMSEA=0.065，Tucker-Lewis 指数 TLI=0.958），由此表明测量模型与样本数据具有较高的适配度，具有较好的拟合优度，构建的测量模型有效。

表 3: 模型整体验证性因素分析结果

拟合指数	**χ2/df**	**GFI**	**AGFI**	**SRMR**	**RMSEA**	**CFI**	**TLI**
数值	2.635	0.854	0.902	0.044	0.065	0.935	0.958
拟合情况	较好	较好	较好	较好	合理	较好	较好

接着，对量表进行进一步地效度分析，观察表 4 可知，所有变量的组合信度 CR 值在 0.857 到 0.902 之间，均高于 0.7，平均方差萃取值 AVE 值在 0.557 和 0.588 之间，均高于 0.5。此外，大部分变量测量题项的标准化因子载荷系数高于 0.7，仅有少部分题项的标准化因子载荷接近 0.7，分别为表征数实融合成效的数字技术运用对人均营业收入的影响，以及衡量绿色创新的企业新产品生产过程中的废物排放，及水、电能源等的消耗等题项，由于其为常见表征指标，且超过临界值 0.5，因此，相关题项仍具有保留价值；综上，本文的测量量表具有较高的聚合效度和良好的内部结构效度。

另外，对于区分效度，本文主要通过比较每个变量 AVE 的平方根与该变量和其他所有变量相关系数大小的绝对值进行判断。所有变量的 AVE 平方根值均大于该变量所在行和列的其他相关系数值，由此表明本文的测量量表具有较高的区分效度。

表 4: 主要变量效度检验结果

变量名称	**题项**	**标准化载荷系数 FL**	**CR**	**AVE**
数实融合	DRI1	0.774	0.857	0.588
	DRI2	0.731		
	DRI3	0.769		
	DRI4	0.784		
	DRI5	0.784		
	DRI6	0.800		
	DRI7	0.804		
	DRI8	0.728		

变量名称	题项	标准化载荷系数 FL	CR	AVE
	DRI9	0.763		
	DRI10	0.803		
	DRI11	0.794		
	DRI12	0.708		
	DRI13	0.626		
知识治理	KG1	0.788	0.867	0.581
	KG2	0.714		
	KG3	0.764		
	KG4	0.764		
	KG5	0.818		
	KG6	0.769		
	KG7	0.745		
	KG8	0.765		
	KG9	0.707		
	KG10	0.801		
	KG11	0.718		
	KG12	0.851		
绿色创新绩效	GIP1	0.802	0.902	0.557
	GIP2	0.705		
	GIP3	0.632		
	GIP4	0.697		
	GIP5	0.747		
	GIP6	0.762		
	GIP7	0.781		
	GIP8	0.802		
	GIP9	0.773		
	GIP10	0.812		

1.3 样本描述性统计

最后，表 5 汇报了本文主要变量的描述性统计，可以看出，所有变量的均值及标准差均处于合理范围之内，并且主要变量之间均存在相关性，为后续回归分析奠定了基础。

表 5: 各变量描述性统计

变量	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
1.企业年龄	1							
2.企业规模	0.402**	1						
3.产权性质	0.108*	0.279**	1					
4.所属行业	-0.039	-0.144**	-0.153**	1				
5.所在地区	0.071	0.118**	-0.074	0.113*	1			
6.数实融合	-0.041	-0.005	-0.05	-0.075	-0.005	0.767		
7.知识治理	0.04	0.06	0.09	0.077	0.063	0.301**	0.762	
8.绿色创新绩效	-0.052	-0.024	-0.052	0.027	-0.055	0.287**	0.405**	0.746
均值	2.342	2.558	0.201	0.248	0.432	3.149	3.102	3.248
标准差	0.914	1.568	0.444	0.471	0.496	1.113	1.178	0.898

注：***p<0.001，**P<0.010，*P<0.050；对角线上的数据是平均方差提取值 AVE 的平方根。

2. 多元回归分析

2.1 数实融合对绿色创新绩效的影响

回归结果如表 6 所示。结果显示，在控制了企业年龄、企业规模、产权性质、所属行业、所在地区的影响下，数实融合的回归系数为 0.285，$p<0.001$，表明数实融合对企业绿色创新绩效存在显著的正向影响。与模型 1 相比，模型 2 的 R^2 有所增加，且 F 值达到显著水平，由此说明模型的构建比较理想。回归结果表明数实融合对企业绿色创新绩效具有显著正向影响，假设 H1 成立。这一结果与已有研究一致（史丹和孙光林，2023），充分证明了数实融合对企业绿色创新绩效的积极推动作用，揭示了在制造企业进行数字化技术的深度推广应用对于生产经营的重要性。

表 6: 基准回归分析

变量	**绿色创新绩效**	
	模型 1	**模型 2**
企业年龄	-0.050	-0.037
企业规模	0.013	0.007
产权性质	-0.046	-0.028
所属行业	0.020	0.044
所在地区	0.107	0.124
数实融合		0.285***
R^2	0.084	0.116
调整 R^2	0.071	0.091
F 值	0.435	6.228***

注：*p<0.05；**p<0.01；***p<0.001。

2.2 基于知识治理的中介效应

关于中介效应的检验，本文遵循 Baron 和 Kenny（1986）的检验方法，首先检验自变量对因变量的影响。其次，检验自变量对中介变量的影响。随后，检验中介变量对因变量的影响。最后，在控制中介变量后，检验自变量对因变量的影响。若在控制中介变量后，自变量对因变量的影响变得不显著，则存在完全中介效应；若在控制中介变量后，自变量对因变量的影响变弱但仍然显著，则存在部分中介效应。

回归结果见表 7。模型 1-2 用来检验数实融合对知识治理的影响。模型 1 为基准模型，用来检验控制变量对知识治理的影响，模型 2 在模型 1 的基础上加入数实融合用于检验其对知识治理的影响。检验结果显示，数实融合的回归系数为 0.296，$p<0.01$，表明数实融合对知识治理存在显著正向影响。与模型 1 相比，模型 2 的 R^2 有所增加，且 F 值显著，由此说明模型的构建比较理想。综上，数实融合对知识治理具有显著的正向影响，假设 H2a 得到验证。

模型 3 用来检验知识治理对绿色创新绩效的影响。结果显示，知识治理对绿色创新绩效存在显著正向影响，系数 0.438，$p<0.01$，同时，F 值显著，模型较为理想。假设 H2b 得到支持。

接下来，将中介变量与自变量同时放入回归方程，结果见模型 5。观察可知，在将中介变量知识治理与数实融合同时放入回归方程后，数实融合系数 0.161，$p<0.01$，对绿色创新绩效的正向影响与模型 4 相比，系数下降，但仍然显著。同时，F 值显著，模型设定较为理想。综上，知识治理在数实融合与绿色创新绩效的关系中存在中介作用，并且观察系数值可知，知识治理发挥部分中介效应。假设 H2 得到验证。

表 7: 知识治理中介效应的回归分析结果

变量	**知识治理**		**绿色创新绩效**		
	模型 1	**模型 2**	**模型 3**	**模型 4**	**模型 5**
企业年龄	0.031*	0.048*	-0.070	-0.037	-0.056
企业规模	-0.016	-0.019	0.016	0.007	0.011
产权性质	0.003	0.011	-0.042	-0.028	-0.028
所属行业	0.033	0.044	0.009	0.044	0.029
所在地区	0.051	0.068	0.014	0.053	0.044
数实融合		0.296**		0.285***	0.161**
知识治理			0.438**		0.419**
R^2	0.010	0.029	0.073	0.086	0.127
调整 R^2	0.001	0.015	0.061	0.072	0.113
F 值	0.783	1.951*	5.234***	6.228***	8.160***

注： *$p<0.05$；**$p<0.01$；***$p<0.001$。

现在，进一步验证知识治理的中介效应，采用 Bootstrap（重复抽样 5000 次）方法进行检验，若 95%置信区间内不包括零，说明中介效应显著，结果见表 8。由表可知数实融合通过知识治理影响制造企业绿色创新绩效的间接效应值为 0.124，且 95%的置信区间 CI=[0.017，0.080]不包含 0，表明知识治理的中介效应显著。以上分析结果为验证 H2 提供了进一步支持。

表 8: 知识治理的中介效应分析

影响路径：数实融合→知识治理→绿色创新绩效			Bootstrap 95%CI	
	效应值	BootSE	LLCI	ULCI
总效应	0.285	0.052	0.182	0.388
直接效应	0.161	0.050	0.264	0.461
间接效应	0.124	0.017	0.014	0.080

注：*p<0.05；**p<0.01；***p<0.001。

综合以上回归过程，本文认为知识治理在数实融合与制造企业绿色创新绩效关系之间发挥着重要中介传导作用，这一检验结论，也揭示了在知识经济社会，知识治理在促进企业创新绩效过程中的重要性。正如已有研究指出，提高知识治理水平可有效解决“卡脖子”问题，激发创新生态系统，知识治理对于企业创新能够产生正向影响（Aslam et al., 2024；许学国等，2025）。知识具有稀缺性、难以模仿性和不可替代性，有效的知识治理和利用对于提升企业绿色创新绩效具有至关重要。总之，通过分析可知，知识治理在数实融合与绿色创新绩效之间发挥中介作用，知识治理已经成为数实融合驱动制造企业绿色创新绩效的一条有效渠道。

讨论

本研究通过实证检验证实数实融合对制造企业绿色创新绩效具有显著正向影响，数实融合程度每提升 1%，绿色创新绩效相应增长 0.285%，这一结果与史丹和孙光林（2023）关于数实融合促进绿色创新的研究结论一致，进一步验证了数字经济与实体经济融合的绿色赋能效应。从作用机制来看，数实融合通过渗透研发、生产、销售全价值链，破解了绿色创新中的信息不对称与资源配置低效难题，其核心逻辑在于数字技术重构了“数据整合-决策优化-价值转化”的创新链条，这与 Fitzgerald et al.（2014）提出的数字化转型赋能企业运营优化理论相契合。

与曹增栋和岳中刚（2024）关注企业绿色化转型的宏观分析不同，本研究细化了数实融合的微观作用路径，揭示了知识治理的中介传导效应，填补了现有研究对数实融合与绿色创新之间传导机制探讨的不足。这一发现呼应了知识基础观的核心观点，即知识是创新的核心资源，而数实融合通过优化知识治理机制，化解了绿色创新中知识共享不畅、转化低效等关键问题，为 Aslam et al.（2024）强调的知识治理对创新的正向作用提供了新的应用情境。

理论层面，本研究拓展了数实融合赋能绿色创新的理论框架，明确了知识治理的中介角色，丰富了对数字技术影响企业可持续发展的认知。实践层面，该结论为制造企业提供了明确指引：通过数字化改造全业务流程、构建高效知识治理体系，可有效提升绿色创新绩效。

总结

本文通过研究数实融合对制造企业绿色创新绩效的影响，并探讨知识治理的中介作用，从理论上拓展了数实融合赋能绿色创新的研究框架，深化了对于数实融合赋能效应的理论认知，进一步，在理论拓展之外，本文主要发现如下，数实融合对制造企业绿色创新绩效具有显著正向影响，且这种影响贯穿企业全价值链，数实融合已成为驱动制造业绿色创新发展的一个有效动力。实证结果表明，数实融合程度每提升 1%，将带来制造企业绿色创新绩效增加 0.285%，随着数实融合不断推进，数字化技术在企业研发、生产、销售、管理等环节的深度渗透，对企业的绿色创新绩效产生直接且显著的促进作用。数实融合能够驱动制造企业绿色创新发展，这一结论彰显了数实融合作为“新型动力要素”对制造业绿色转型的赋能价值，揭示了数字经济与实体经济融合在破解绿色创新“高成本、高风险”困境中的实践意义。知识治理在数实融合与绿色创新绩效间发挥中介作用，知识治理已经成为数实融合驱动制造企业绿色创新绩效的一条有效渠道。

本研究也存在一些局限性，一方面尽管样本覆盖多个省份，但样本范围仍较为局限。中国地域广阔，东、中、西部地区的经济发展水平、数字化基础和环境治理压力差异显著，因此，研究结果的普适性存在局限。另一方面，本文并未对数实融合与绿色创新绩效可能存在的“双向因果”关系进行处理，可能存在模型内生性问题，以及时间截面回归带来的不足。

未来，可以考虑引入时间动态研究，开展数实融合与绿色创新绩效的研究，探讨两者关系的动态演化规律。可以采用案例跟踪法，选取典型企业进行长期观察，分析数实融合从初步应用到深度融合的不同阶段，知识治理机制的变化及其对绿色创新绩效的影响。

建议

第一，政府层面要加快构建数实融合与绿色创新的政策支持体系。要不断完善数字基础设施建设，解决当前中国数字基础设施存在的区域发展不均衡、行业渗透不充分、应用场景不丰富等问题，制定分区域、分行业的数字基础设施建设路线图，重点支持中西部地区制造业集聚区的数字化改造。鼓励知识创新平台共建和共享，针对知识治理的中介作用，政府应搭建跨组织的知识协同平台，降低企业知识获取与共享成本。

第二，企业层面要多维度依托数实融合驱动绿色创新。制造企业应将数实融合与绿色创新纳入企业总体战略规划，建立数字赋能-知识治理-绿色创新协同机制，从基础设施、技术应用、人才建设三方面制定分阶段路线图。企业要注重在生产经营全流程对于数字技术和绿色创新的实践，围绕研发、生产、销售、管理环节嵌入数字技术，实现降本、增效、减碳；特别地，在管理环节要注重引入 ERP 与 EMS 集成方案，实现运营与环境数据联动。构建数字化知识治理体系，针对知识治理在数实融合与绿色创新过程中的重要性，企业要积极依托数字技术，打破知识壁垒，注重内部知识挖掘以及外部知识获取，优化知识治理机制，发挥知识的中介传导作用。

第三，市场层面要营造数实融合与绿色创新的生态。推动行业绿色创新标准共建，鼓励行业内企业、协会、科研机构联合组建绿色创新联盟，以数实融合技术为纽带推动标准共建与资源共享，标准制定-认证监督-市场认可闭环。强化消费者绿色消费认知，通过信息透明化、

选择便捷化、价值感知化引导消费者优先选择数实融合绿色产品。依托数字工具扩散知识并转化为市场力量，搭建绿色需求-企业创新对接平台，形成需求-响应-落地-反馈闭环，让知识转化为企业创新动力，实现绿色市场与创新能力双向提升。

致谢

本文受到广西高校中青年教师科研基础能力提升项目（2022KY0635），广西哲学社会科学项目（24JYC001）的资助。

参考文献

Aslam, M. S., Qammar, A., Ali, I., Yaqub, M. Z., Ahmed, F., & Mohapatra, A. K. (2024). Fostering innovation speed and quality in ICT firms: The role of knowledge governance mechanisms, absorptive capacity and environmental dynamism. Technological Forecasting and Social Change, 205, 123460.

Fitzgerald, M., Kruschwitz, N., Bonnet, D., & Welch, M. (2014). Embracing digital technology: A new strategic imperative. MIT Sloan Management Review, 55(2), 1-12.

Goldfarb, A., & Tucker, C. (2019). Digital economics. Journal of Economic Literature, 57(1), 3-43.

Gooderham, P., Minbaeva, D. B., & Pedersen, T. (2011). Governance mechanisms for the promotion of social capital for knowledge transfer in multinational corporations. Journal of Management Studies, 48(1), 123-150.

Grandori, A. (2001). Neither hierarchy nor identity: Knowledge-governance mechanisms and the theory of the firm. Journal of Management and Governance, 5(3), 381-399.

Ruiz-Jiménez, J. M., & Fuentes-Fuentes, M. D. M. (2016). Management capabilities, innovation, and gender diversity in the top management team: An empirical analysis in technology-based SMEs. BRQ Business Research Quarterly, 19(2), 107-121.

Sun, G., Li, T., Ai, Y., & Li, Q. (2023). Digital finance and corporate financial fraud. International Review of Financial Analysis, 87, 102566.

石玉堂, 王晓丹, & 周十同. (2025). 数字经济与实体经济融合发展的就业效应研究. 北京工业大学学报(社会科学版), (1), 36-55.

史丹, & 孙光林. (2023). 数字经济和实体经济融合对绿色创新的影响. 改革, (2), 1-13.

白景坤, 李思晗, & 李红艳. (2022). 开放视角下企业的知识治理和隐性知识治理. 科研管理, (1), 143-152.

邝劲松, & 彭文斌. (2020). 数字经济驱动经济高质量发展的逻辑阐释与实践进路. 探索与争鸣, (12), 132-200.

朱瑞博. (2025). 数字经济和实体经济深度融合的核心要义、制度障碍与体制机制创新. 上海经济研究, (1), 5-18.

向阳, & 曹勇. (2015). 企业创新网络知识治理与知识转移：基于战略性新兴产业的实证研究. 管理评论, (9), 48-58.

池毛毛, 叶丁菱, 王俊晶 & 翟姗姗. (2020). 中国中小制造企业如何提升新产品开发绩效——基于数字化赋能的视角. 南开管理评论, 23(3), 63-75.

许学国, 周诗雨, & 刘凤梅. (2025). 考虑技术势差的创新生态系统知识治理研究. 科研管理, (1), 12-23.

杜金柱, & 扈文秀. (2023). 数字经济发展对企业创新持续性的影响. 统计与决策, (3), 21-26.

李佳轩, & 储节旺. (2024). 数智化知识价值链的概念缘起、理论模型与内外动因. 情报理论与实践, 47(9), 70-146.

杨东亮, & 丁晨曦. (2024). 数实融合赋能经济高质量发展：要素型融入与技术型融入. 商业研究, (6), 77-90.

吴建祖, & 马晴. (2025). CEO-TMT 交互、绩效期望落差与企业环境战略. 管理评论, 37(6), 174-186.

宋华, 韩梦玮, & 胡雪芹. (2023). 供应链金融如何促进供应链低碳发展?——基于国网英大的创新实践. 管理世界, 39(5), 93-112.

张沥幻, & 张金昌. (2024). 数实技术融合、企业转型升级与新质生产力——基于 A 股制造企业的实证检验. 科技进步与对策, 41(20), 1-12.

张倩, 翟介宇, & 邢志华. (2024). 数实融合驱动制造企业价值链重构——基于宁德时代的纵向单案例研究. 现代管理科学, (6), 155-163.

周文, & 施炫伶. (2023). 中国式现代化与数字经济发展. 财经问题研究, (6), 3-15.

周密, 王雷, & 郭佳宏. (2024). 新质生产力背景下数实融合的测算与时空比较——基于专利共分类方法的研究. 数量经济技术经济研究, 41(7), 5-27.

胡石其, & 熊磊. (2018). “组织学习” 驱动绿色创新绩效的影响机制. 求索, (6), 82-88.

施锦诚, 朱凌, & 梅景瑶. (2023). 关键共性技术攻关产学研联盟实现突破性创新的机制研究. 科研管理, (12), 104-114.

徐建中, 贯君, & 林艳. (2017). 制度压力、高管环保意识与企业绿色创新实践——基于新制度主义理论和高阶理论视角. 管理评论, (9), 72-83.

曹增栋, & 岳中刚. (2024). 数实融合与企业绿色化转型. 商业研究, (6), 20-29.

崔琳昊, & 冯烽. (2024). 数实融合与城市绿色发展：影响与机制. 上海财经大学学报, (4), 49-63.

揭筱纹, & 宁胜男. (2021). “双循环” 背景下中国中小制造企业绿色国际竞争力多维模式构建. 企业经济, (10), 14-23.

解学梅, & 朱琪玮. (2021). 企业绿色创新实践如何破解 “和谐共生” 难题? 管理世界, (1), 128-149.

ANALYSIS AND PREDICTION OF KRW/USD EXCHANGE RATE USING SOUTH KOREAN SECTORAL STOCK DATA WITH MULTIPLE LINEAR REGRESSION

**Pannet Injai[1], Tullatorn Nonmai[2],
Poramate Teerawattanas[3], and Saifon Chaturantabut[4*]**

[1,2,3,4]Department of Mathematics and Statistics, Faculty of Science and Technology, Thammasat University, Rangsit Campus, Thailand
[*]**Corresponding Author, E-mail:** saifon@mathstat.sci.tu.ac.th

Abstract

This study applies Multiple Linear Regression (MLR) to predict trends in the Korean Won to US Dollar (KRW/USD) exchange rate using data from key industrial sectors in South Korea. The stock prices of different companies in the entertainment, technology, and consumer goods sectors are considered in the MLR models. The method of backward elimination is employed to select the relevant predictors for the exchange rate with different train-test splits. The predictive model achieved high accuracy, with a Mean Absolute Percentage Error (MAPE) of 1.66% when using a data split of 90% training data and 10% testing data. In this case, the MLR model is given by KRW/USD = $1476.18 + 1.449X_2 - 2.230X_5 - 1.544X_7 - 1.070X_8 + 3.267X_9 - 0.447X_{10}$, where X_2, X_5, X_7 X_8 X_9 and X_{10} are the stock prices of JYP Entertainment, Studio Dragon, Seoul Broadcasting System, HYBE Corporation, Kakao Corporation, and Amorepacific, respectively. In addition, this work proposes a practical regression model that uses historical stock prices to estimate the future KRW/USD exchange rate. The corresponding MAPE accuracy is roughly 2%. These findings suggest that sectoral stock data can effectively serve as independent variables for forecasting exchange rates.

Keywords: Multiple Linear Regression, KRW/USD Exchange Rate, Exchange Rate Forecasting, Stock Prices

Introduction

The exchange rate is a critical economic variable influencing the stability of national economies, particularly for export-dependent nations like South Korea. The fluctuation of the Korean Won against the US Dollar (KRW/USD) directly impacts revenue, operational costs, and global competitiveness across key sectors, including entertainment, digital content, technology, and consumer goods manufacturing. Between 2022 and 2023, the KRW exhibited higher volatility compared to historical trends, driven by external pressures such as the Federal Reserve's interest rate hikes, global inflation, geopolitical tensions, and post-COVID-19 economic recovery. These fluctuations necessitate robust forecasting models to mitigate risks related to profitability and cost management for businesses and investors.

While extensive research exists on exchange rate forecasting, the majority of studies rely on macroeconomic variables such as GDP, CPI, and interest rates. These macro-level indicators often fail to capture the specific sensitivities of distinct industrial sectors. The South Korean economy is structurally unique, with heavy reliance on specific industries like K-Pop entertainment (e.g., S.M. Entertainment, HYBE Corporation) and technology (e.g., Kakao Corporation). These companies generate significant foreign revenue, making their stock prices highly responsive to currency movements. Currently, there is a lack of research utilizing daily sectoral stock data to predict KRW/USD trends, creating a gap in understanding how micro-level market data influences macro-level currency values.

Research Objectives

This study aims to bridge this gap by applying Multiple Linear Regression (MLR) to daily stock price data from 10 major South Korean companies. The primary objectives are:

1. To analyze the relationship between historical stock prices of key industrial sectors and the KRW/USD exchange rate.
2. To construct and validate a predictive model for the KRW/USD exchange rate using stock prices of companies from major industrial sectors.

Literature Review

The research works regarding the interplay between equity markets and foreign exchange rates are primarily framed by two competing theoretical paradigms: the "flow-oriented" model and the "portfolio balance" model. The flow-oriented model, rooted in the work of Dornbusch and Fischer (1980), posits that causality flows from exchange rates to stock prices. This perspective argues that currency depreciation boosts a nation's export competitiveness and corporate earnings, thereby elevating stock valuations. Conversely, the portfolio balance approach, developed by Branson (1983) and Frankel (1983), suggests the reverse causality—that stock prices drive exchange rates. In this framework, rising domestic stock prices attract foreign capital seeking higher returns, which increases the demand for the local currency and leads to its appreciation.

Empirical research utilizing these frameworks has yielded mixed results, often contingent upon the economic structure of the nation in question. Supporting the flow-oriented hypothesis, Aggarwal (1981) identified a significant correlation where the U.S. dollar's movement influenced stock prices, a finding echoed by Abdalla and Murinde (1997) in emerging markets like India, where currency volatility was found to dictate firm valuations. In the context of the Thai Baht (THB) and Chinese Yuan (CNY) exchange rate, empirical research has consistently emphasized the critical role of fundamental macroeconomic variables. Srisangngam and Khongsawatkiat (2016) laid the groundwork by identifying that key economic indicators—specifically interest rates, inflation differentials, and GDP growth—serve as statistically significant determinants of the THB/CNY exchange rate, supporting the classical monetary approach to currency valuation. Building upon this foundation, Glakiatnarong et al. (2022) revisited these relationships using more recent datasets, confirming that despite global economic shifts, these fundamental factors remain the primary drivers of currency fluctuation between the two nations. In contrast, supporting the portfolio balance model, Granger, Huang, and Yang (2000) found that in the Philippines, stock price movements actually preceded exchange rate changes, suggesting that in certain Asian economies, capital flows driven by equity performance are a dominant driver of currency value. Further complicating this connection are findings of bidirectional causality, particularly within East Asia; Pan et al. (2007) highlighted dynamic linkages during periods of financial instability, noting that information is often processed simultaneously by both equity and currency markets in the region. The work done by Pan, M. S., Fok, R. C. W., and Liu, Y. A. (2006).

In the specific context of South Korea, recent literature has begun to explore the distinct economic footprint of the cultural sector, moving beyond traditional manufacturing-based analysis. Park (2023) examined the role of K-Pop as a critical economic engine, demonstrating its transition from a cultural trend to a significant driver of national brand value and capital inflows. Similarly, Parc

(2021) analyzed the broader trade implications of the "Hallyu" wave, arguing that cultural exports now command a unique influence on Korea's balance of payments. However, current forecasting models often remain tethered to broad market indices; for instance, Lee (2023) investigated the synchronization between the KOSPI volatility index and market returns but did not isolate specific high-growth sectors. Consequently, a distinct methodological gap remains in analyzing how specific industrial micro-data—particularly from the entertainment and technology sectors—predicts currency fluctuations. This research addresses this deficiency by applying the microstructure approach to sectoral stock data for predicting the KRW/USD exchange rate.

Research Methodology

Regression Analysis

The core analytical tool employed is Multiple Linear Regression (MLR). This statistical method is used to model the linear relationship between the dependent variable (exchange rate) and multiple independent variables (stock prices). The general regression equation is defined as:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \epsilon,$$

where:

- Y = Predicted KRW/USD Exchange Rate,
- β = Y-intercept (Constant),
- $\beta_1, \ldots, \beta_n$ = Regression coefficients representing the change in Y for a one-unit change in the respective X,
- $X_1, \ldots, X_n$ = Daily stock prices of the selected companies,
- ϵ = Error term.

Prediction Model Construction

To build an optimal prediction model, the study utilized **Backward Elimination**. This iterative process involves:

1. Initially including all 10 independent variables in the model.
2. Testing the statistical significance of each variable.
3. Step-by-step removal of variables that are not statistically significant (typically those with a p-value > 0.05).
4. Retaining only the variables that have a significant impact on the dependent variable to ensure the model is both parsimonious and accurate.

Train-Test Split

To validate the model's predictive accuracy, the dataset was divided into two distinct sets.

- **Training Set:** Used to train the regression model and calculate the coefficients.
- **Testing Set:** A reserved portion of the data (e.g. the final **10%** of the dataset) used to evaluate the model's performance on unseen data. Performance can be measured using the Mean Squared Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) on the test data, indicating high predictive accuracy.

Model Fit and Explanatory Power (R^2)

To evaluate the goodness of fit for the Multiple Linear Regression (MLR) models, this study utilizes the Coefficient of Determination, denoted as R^2. This statistic provides a measure of how well the independent variables (stock prices) account for the fluctuations in the dependent variable (KRW/USD exchange rate). Mathematically, R^2 represents the proportion of the variance in the dependent variable that is predictable from the independent variables. It is calculated as:

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}}$$

- SS_{res} is the sum of squares of residuals (the unexplained variation),
- SS_{tot} is the total sum of squares (the total variance in the data).

Total Sum of Squares (SS_{tot})

This represents the total variability in the dependent variable. It measures how much the observed data points (y_i) differ from the mean of the data ($\bar{y}$). It is calculated as:

$$SS_{tot} = \sum_{i=1}^{n} (y_i - \bar{y})^2 .$$

Sum of Squared Residuals (SS_{res})

Also known as the "Sum of Squared Errors" (SSE), this measures the variability that the regression model *failed* to explain. It is the sum of the squared differences between the actual observed data (y_i) and the values predicted by the model ($\hat{y}_i$). It is calculated as: .

$$SS_{res} = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

In general, the value of R^2 is between 0 and 1. When $R^2 = 1$, the model explains 100% of the variance in the dependent variable. All data points lie perfectly on the regression line. When $R^2 = 0$, the model explains none of the variance. The model is no better than simply predicting the mean ($\bar{y}$) for every observation. Adding more independent variables to the regression model will generally increase or maintain the R^2 value, even if the new variable is not statistically significant. This is a known limitation, often addressed by using the adjusted R-squared.

The adjusted R-squared is a modified version of R-squared that adjusts for the number of predictors in a regression model. It is defined as:

$$R^2_{adj} = 1 - (1 - R^2)\frac{n-1}{n-p-1}$$

- R^2 is the sample R-squared of the model,
- n is the total number of observations (data points),
- p: The number of independent variables (predictors) in the model.

Notice that the adjusted R-squared fixes this by introducing a penalty for adding variables. If a new variable is useful, it increases the model's predictive power enough to outweigh the penalty and the adjusted R-squared increases. If a new variable is useless, the penalty outweighs the tiny gain in standard R^2 and the adjusted R-squared decreases.

Correlation Coefficient

To establish the preliminary relationship between variables, this study employs the Pearson Correlation Coefficient r, which is a statistical measure used to evaluate the strength and direction of the linear relationship between two continuous variables. The coefficient ranges from -1 to +1, offering the following interpretations:

- $r = 1$ (Perfect Positive Correlation): Indicates that as one variable increases, the other increases in exact proportion.
- $r = -1$ (Perfect Negative Correlation): Indicates that as one variable increases, the other decreases in exact proportion.
- $r = 0$ (No Correlation): Indicates no linear relationship between the variables.

In the context of this research, a strong positive correlation suggests that a rise in a specific company's stock price is associated with the depreciation of the Won (higher KRW/USD rate), while a strong negative correlation suggests it is associated with the appreciation of the Won (lower KRW/USD rate). This step is crucial for identifying which variables hold potential predictive power before incorporating them into the Multiple Linear Regression model.

The Pearson Correlation Coefficient (r) for a sample is calculated using the covariance of the two variables divided by the product of their standard deviations. The formula is defined as follows:

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

- r = Pearson Correlation Coefficient
- n = Number of observations (sample size)
- x_i = Individual value of the variable x
- $\bar{x}$ = Mean (average) of the variable x
- y_i = Individual value of the variable y
- $\bar{y}$ = Mean (average) of the dependent variable y.

Variance Inflation Factor

The Variance Inflation Factor (VIF) is a statistical measure used to detect the severity of multicollinearity in a Multiple Linear Regression model. Multicollinearity occurs when two or more independent variables are highly correlated with one another, making it difficult for the model to isolate the individual effect of each variable on the dependent variable. The "Inflation" in VIF refers to the increase in the variance of the estimated regression coefficients caused by this correlation. High multicollinearity can lead to unstable coefficients and statistically insignificant results, even when the variable is theoretically important. The VIF for a specific independent variable (X_i) is calculated using the Coefficient of Determination R_i^2 derived from regressing that specific variable against all other independent variables in the model. The formula is:

$$VIF_i = \frac{1}{1 - R_i^2}$$

where:

- VIF_i: The Variance Inflation Factor for the i-th independent variable,
- R_i^2: The coefficient of determination obtained from an "auxiliary regression" where X_i is treated as the dependent variable and regressed against all other remaining independent variables $X_1, X_2, \ldots, X_{i-1}, X_{i+1}, \ldots, X_n$

As R^2 approaches 1 (indicating X_i is highly predicted by other variables), the denominator 1-R^2approaches 0, causing the VIF value to approach infinity. VIF values can be interpreted as follows:

- VIF = 1: No correlation between the independent variable and other variables.
- 1 < VIF < 10: Moderate correlation; generally acceptable.
- VIF $\geq$ 10: High correlation; indicates multicollinearity, suggesting that the variable should likely be removed or combined to improve model stability.

Accuracy Measurements

The accuracy of the prediction will be measured by the Mean Squared Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) given below:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100\%$$

where n is the total number of observations, y_i is the actual value for the i-th observation, and $\hat{y}_i$ is the predicted value for the i-th observation.

Results

This section presents the empirical findings obtained from the Multiple Linear Regression (MLR) analysis. This work considers quantitative secondary data collected on a daily basis over a two-year period from 2022 to 2023. To predict the KRW/USD exchange rate, this work considers daily closing stock prices over a two-year period during 2022 and 2023 of 10 major South Korean companies (from Yahoo Finance) representing key sectors such as entertainment, technology, and consumer goods. The specific companies selected are:

1. S.M. Entertainment Co.
2. JYP Entertainment
3. LG Household & Healthcare
4. CJ ENM Co. Ltd
5. Studio Dragon
6. Jcontentree
7. SBS (Seoul Broadcasting System)
8. HYBE Corporation
9. Kakao Corporation
10. Amorepacific.

The selected companies above represent the powerhouse engines driving South Korea's "Hallyu" (Korean Wave) and consumer export economy, spanning the critical sectors of entertainment, technology, and lifestyle goods. The entertainment cluster is anchored by K-pop giants S.M. Entertainment, JYP Entertainment, and HYBE Corporation, alongside major media conglomerates CJ ENM, Studio Dragon, Jcontentree (ContentreeJoongAng), and the broadcaster SBS, all of which are instrumental in producing globally consumed music, film, and television content. Complementing this ecosystem is Kakao Corporation, a dominant technology platform integrating messaging and digital content, while the consumer goods sector is led by rival conglomerates LG Household & Healthcare and Amorepacific, which command the international market for luxury cosmetics and daily necessities. Collectively, these firms rely heavily on global revenue streams, making their stock performance highly sensitive to exchange rate fluctuations and indicative of the broader health of South Korea's export-driven economy. The trends of these stock prices over the year 2022 and 2023 are shown in Figure 1.

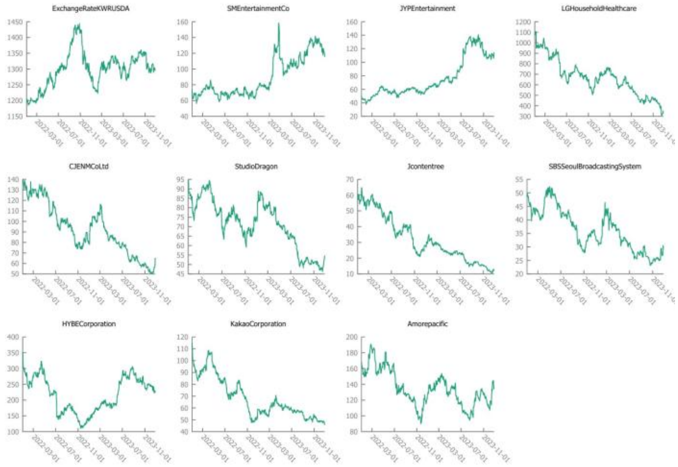
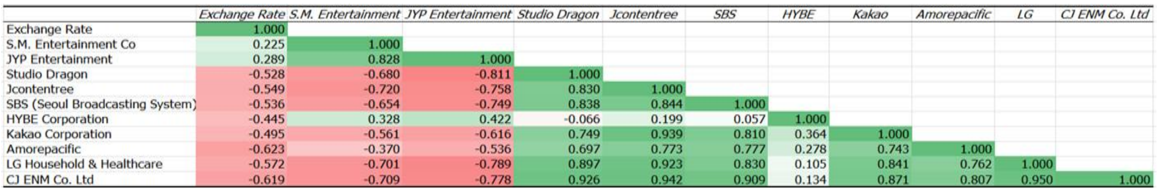


Figure 1: Fluctuations in the KRW/USD exchange rate and stock prices of key South Korean companies from 2022 to 2023, including SM Entertainment, JYP Entertainment, HYBE Corporation, Kakao Corporation, Studio Dragon, CJ ENM, Jcontentree, SBS, LG Household & Healthcare, and Amorepacific.

To verify the linear relationships between the variables and identify potential multicollinearity, a Pearson Correlation Matrix is generated and shown in Figure 2 below.



	Exchange Rate	*S.M. Entertainment*	*JYP Entertainment*	*Studio Dragon*	*Jcontentree*	*SBS*	*HYBE*	*Kakao*	*Amorepacific*	*LG*	*CJ ENM Co. Ltd*
Exchange Rate	1.000										
S.M. Entertainment Co	0.225	1.000									
JYP Entertainment	0.289	0.828	1.000								
Studio Dragon	-0.528	-0.680	-0.811	1.000							
Jcontentree	-0.549	-0.720	-0.758	0.830	1.000						
SBS (Seoul Broadcasting System)	-0.536	-0.654	-0.749	0.838	0.844	1.000					
HYBE Corporation	-0.445	0.328	0.422	-0.066	0.199	0.057	1.000				
Kakao Corporation	-0.495	-0.561	-0.616	0.749	0.939	0.810	0.364	1.000			
Amorepacific	-0.623	-0.370	-0.536	0.697	0.773	0.777	0.278	0.743	1.000		
LG Household & Healthcare	-0.572	-0.701	-0.789	0.897	0.923	0.830	0.105	0.841	0.762	1.000	
CJ ENM Co. Ltd	-0.619	-0.709	-0.778	0.926	0.942	0.909	0.134	0.871	0.807	0.950	1.000

Figure 2: Pearson Correlation Matrix Heatmap

As illustrated in Figure 2, distinct directional relationships exist between the variables. Stocks such as Studio Dragon and HYBE Corporation displayed strong negative correlations (represented by darker red tones in Figure 2) with the exchange rate. This suggests that an appreciation in these "K-

Wave" export stocks generally coincides with a strengthening of the Korean Won. Conversely, JYP Entertainment showed a positive correlation, indicating that its stock price movement aligns with a depreciating Won.

Before performing the regression analysis, the distributional properties of the dependent variable (KRW/USD exchange rate) and the independent variables (stock prices) are analyzed to understand their volatility and central tendencies.

Table 1: Descriptive Statistics of KRW/USD Exchange Rate and Sectoral Stock Prices (2022–2023)

Variable	Mean	Maximum	Minimum	Std. Deviation
Exchange Rate KRW/USD	1298.7	1444.6	1185.9	56.611
S.M Entertainment	89.812	158.50	56.000	24.826
JYP Entertainment	75.644	141.10	38.350	27.798
LG Household Health	663.90	1104.0	311.00	168.69
CJ ENM Co. Ltd	92.170	140.00	50.200	24.262
Studio Dragon	71.162	94.600	46.100	12.863
Jcontentree	32.008	64.600	10.570	14.329
SBS Seoul Broadcasting	36.208	52.400	23.100	7.7181
HYBE Corporation	217.42	350.50	109.50	56.306
Kakao Corporation	67.908	114.50	45.650	16.933
Amorepacific	134.13	191.00	89.700	22.140

Table 1 presents the summary statistics for the dataset. The results indicate significant volatility within the technology and entertainment sectors. Specifically, stocks such as Kakao Corporation and HYBE Corporation exhibited higher standard deviations compared to consumer goods stocks like Amorepacific. This higher volatility reflects their sensitivity to global market sentiment. Furthermore, as shown in Table 1, the KRW/USD exchange rate demonstrated a wide range between its minimum and maximum values, underscoring the period of macroeconomic instability driven by external factors such as global inflation.

Regression Models.

The multiple linear regression model is used with the backward elimination approach to select the variables in the regression models. The general form of the initial regression model for predicting the exchange rate KRW/USD is given by

$$KRW/USD = A + B_1X_1 + B_2X_2 + B_3X_3 + B_4X_4 + B_5X_5 + B_6X_6 + B_7X_7 + B_8X_8 + B_9X_9 + B_{10}X_{10},$$

where A is a constant,
B_i is the coefficient from regression for the variables X_i, $i=1,2,\ldots,10$
X_1 is the stock price of S.M. Entertainment Co
X_2 is the stock price of JYP Entertainment
X_3 is the stock price of LG Household & Healthcare
X_4 is the stock price of CJ ENM Co. Ltd
X_5 is the stock price of Studio Dragon
X_6 is the stock price of Jcontentree
X_7 is the stock price of SBS (Seoul Broadcasting System)
X_8 is the stock price of HYBE Corporation
X_9 is the stock price of Kakao Corporation
X_{10} is the stock price of Amorepacific

In this work, we consider 4 models. There are 3 different train-test splits, train90%-test10%, train80%-test20%, and train70%-test30%. The last model predicts the exchange rate by using available previous week daily stock prices. Each case of these provides a different regression model based on the selected variable from the backward elimination steps.

Model 1: Train 90%-Test 10%

To construct this model, from a total of 516 data points, we use the first 464 data points (90%) for training and the remaining 52 data points (10%) for testing. In this case, the resulting regression model based on backward elimination with significant level 0.05 for all independent variables is given below.

$$\text{KRW/USD} = 1476.18 + 1.449X_2 - 2.230X_5 - 1.544X_7 - 1.070X_8 + 3.267X_9 - 0.447X_{10}$$

where KRW/USD is the Korean Won to US Dollar exchange rate,
X_2 is the stock price of JYP Entertainment,
X_5 is the stock price of Studio Dragon,
X_7 is the stock price of SBS (Seoul Broadcasting System),
X_8 is the stock price of HYBE Corporation,
X_9 is the stock price of Kakao Corporation,
X_{10} is the stock price of Amorepacific.

Figure 3: [Model 1: Train90%-Test10%] Comparison of actual vs. predicted KRW/USD exchange rate (training set) and the predicted exchange rate of test set with 95% confidence interval.

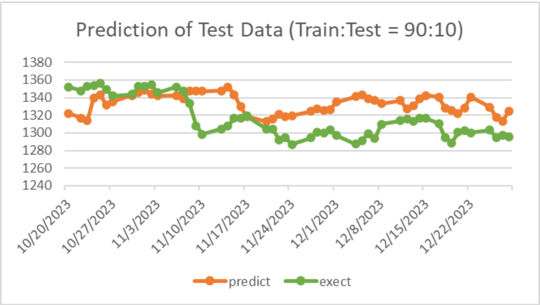


Figure 4: [Model 1: Train 90% - Test 10%] Comparison of actual vs. predicted KRW/USD exchange rate (test data set).

Table 2: The Variance Inflation Factor (VIF) of each independent variable in Model 1.

Independent Variables in Model 1	**VIF**
X_2 : Stock price of JYP Entertainment	**8.449**
X_5 : Stock price of Studio Dragon	4.264
X_7 : Stock price of SBS	4.755
X_8 : Stock price of HYBE	5.881
X_9 : Stock price of Kakao	6.967
X_{10} : Stock price of Amorepacific.	3.913

Figure 3 presents a comparative time-series analysis of the daily closing values for the KRW/USD exchange rates and their predicted values using Model 1. Notice that the trend of both actual and predicted exchange rates are mostly in the same direction. Based on Figure 3, notice that the prediction tracks the trends of the actual values closely. Although there are discrepancies in certain intervals, the results reflect the model's ability to effectively capture the directional movement of the data. Furthermore, it projects future trends within a 95% confidence interval, indicating an acceptable level of forecasting uncertainty. Based on using 90% training data, Model 1 has corresponding R-squared of 0.682 , adjusted R-squared of 0.678, RMSE of 33.154, and standard error of regression 33.407, as given in Table 2 for Model 1.

Figure 4 presents the forecast for the exchange rates for the 10% test data from Model 1. It shows that Model 1 successfully simulates future trends that align with actual values. Based on the accuracy evaluation of the Model 1 on the 10% test set, the results yielded a Mean Squared Error (MSE) of 777.184, a Root Mean Squared Error (RMSE) of 27.8780, a Mean Absolute Error (MAE) of 24.3864, and a Mean Absolute Percentage Error (MAPE) of 1.8639%. These results demonstrate that the model exhibits a relatively low average error, both in terms of absolute difference (MAE) and percentage error (MAPE), the latter of which remains below 2%. This indicates that the model possesses strong accuracy in predicting trends and is suitable for effective forecasting. Table 2 shows the values of VIF for all variables in Model 1, which reflects no multicollinearity issue since all VIF values are less than 10.

Model 2: Train 80% - Test 20%

To construct this model, from a total of 516 data points, we use the first 413 data points (80%) for training and the remaining 103 data points (20%) for testing. In this case, the resulting multiple linear regression model based on backward elimination with significant level 0.05 for all independent variables is given below.

$$\text{KRW/USD} = 1467.01 + 1.628X2 - 2.307X5 - 1.405X7 - 1.092X8 + 3.440X9 - 0.514X10$$

where KRW/USD is the Korean Won to US Dollar exchange rate,
X_2 is the stock price of JYP Entertainment
X_5 is the stock price of Studio Dragon
X_7 is the stock price of SBS (Seoul Broadcasting System)
X_8 is the stock price of HYBE Corporation

X_9 is the stock price of Kakao Corporation
X_{10} is the stock price of Amorepacific

Figure 5: [Model 2: Train 80%-Test 20%] Comparison of actual vs. predicted KRW/USD exchange rate (training set) and the predicted exchange rate of test set with 95% confidence interval.

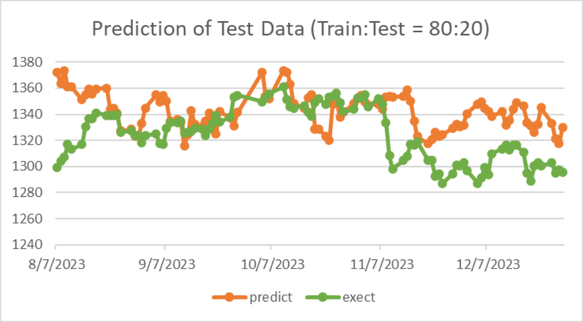


Figure 6: [Model 2: Train 80%-Test 20%] Comparison of actual vs. predicted KRW/USD exchange rate (test data set).

Table 3: The Variance Inflation Factor (VIF) of each independent variable in Model 2.

Independent Variables in Model 2	**VIF**
X_2 : Stock price of JYP Entertainment	3.943
X_5 : Stock price of Studio Dragon	2.795
X_7 : Stock price of SBS	3.792
X_8 : Stock price of HYBE	5.337
X_9 : Stock price of Kakao	6.403
X_{10} : Stock price of Amorepacific.	4.319

Figure 5 shows a comparison of the daily closing values for the KRW/USD exchange rates and their predicted values using Model 2. Similar to Figure 3, notice from Figure 5 that the prediction tracks the trends of the actual values with some discrepancies in certain intervals. Based on using 80% training data, Model 2 has the values for R-squared of 0.679 , adjusted R-squared of 0.674, RMSE of 34.386, and standard error of regression 34.681, as given in Table 2 for Model 2.

Figure 6 presents the future forecast for the exchange rates. It shows that Model 2 successfully simulates future trends that align with actual values. Based on the accuracy evaluation of the Model 2 on the 20% test set, the results yielded a Mean Squared Error (MSE) of 779.8137, a Root Mean Squared Error (RMSE) of 27.925, a Mean Absolute Error (MAE) of 21.842, and a Mean Absolute Percentage Error (MAPE) of 1.664%. This demonstrates that Model 2 provides accurate prediction for the test data set. Table 3 shows the values of VIF for all variables in Model 2, which reflects no multicollinearity issue since all VIF values are less than 10.

Model 3 : Train 70% - Test 30%

To construct this model, from a total 516 data points, we use the first 361 data points (70%) for training and the remaining 155 data points (30%) for testing. In this case, the resulting multiple linear regression model based on backward elimination with significant level 0.05 for all independent variables is given below.

$$\text{KRW/USD} = 1457.50 + 3.098X2 - 3.483X5 - 1.708X7 - 0.793X8 + 3.555X9 - 0.806X10$$

where KRW/USD is the Korean Won to US Dollar exchange rate,
X_2 is the stock price of JYP Entertainment,
X_5 is the stock price of Studio Dragon,
X_7 is the stock price of SBS (Seoul Broadcasting System),
X_8 is the stock price of HYBE Corporation,
X_9 is the stock price of Kakao Corporation,
X_{10} is the stock price of Amorepacific.

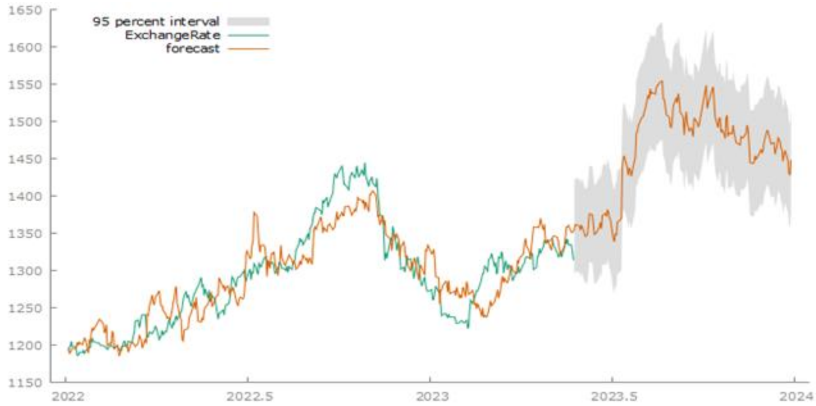


Figure 7: [Model 3: Train 70%-Test 30%] Comparison of actual vs. predicted KRW/USD exchange rate (training set) and the predicted exchange rate of test set with 95% confidence interval.

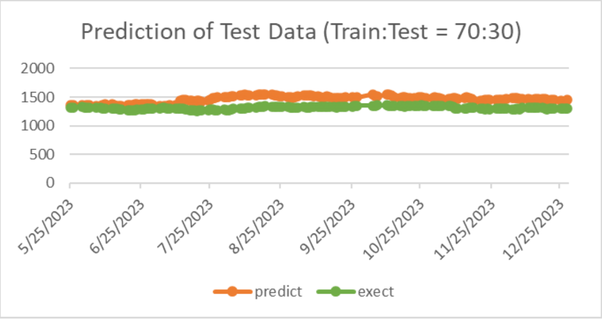


Figure 8: [Model 3: Train 70%-Test 30%] Comparison of actual vs. predicted KRW/USD exchange rate (test data set).

Table 4: The Variance Inflation Factor (VIF) of each independent variable in Model 3.

Independent Variables in Model 3	**VIF**
X_2 : Stock price of JYP Entertainment	1.455
X_5 : Stock price of Studio Dragon	2.740
X_7 : Stock price of SBS	2.878
X_8 : Stock price of HYBE	11.549
X_9 : Stock price of Kakao	7.763
X_{10} : Stock price of Amorepacific.	4.241

Figure 7 compares the daily closing values for the KRW/USD exchange rates and their predicted values using Model 3. Similar to Figures 3 and 5, Figure 7 illustrates that the prediction tracks the trends of the actual values with some discrepancies in certain intervals. Based on using 70% training data, Model 3 has the values for R-squared of 0.768 , adjusted R-squared of 0.764, RMSE of 31.106, and standard error of regression 31.412, as given in Table 2 for Model 3.

Figure 8 presents the future forecast for the exchange rates for the test data. Based on the accuracy evaluation of the Model 2 on the 20% test set data set shown in Figure 8, the results yielded a Mean Squared Error (MSE) of 24574.95, a Root Mean Squared Error (RMSE) of 156.764, a Mean Absolute Error (MAE) of 147.354, and a Mean Absolute Percentage Error (MAPE) of 11.2181%. Notice that, although Model 3 seems to be the most accurate for predicting the training data when compared to Model 1 and Model 2, it has the least prediction accuracy for the test data set. Table 4 shows the values of VIF for all variables in Model 3, which reflects a mild multicollinearity issue since the VIF value of X_8 is slightly larger than 10.

Notice that, from Models 1-3, in order to predict an exchange rate on a given day, the stock prices of the companies on the same day must be used. These models therefore may not be practical for future prediction, since these stock prices are generally not available in advance. The next model considers the stock prices from the past week to construct a predictive regression model. As a result, to predict an exchange rate for a given day, this model uses the stock prices of the selected companies from the previous week ,which are generally available in advance.

Model 4: Model for forecasting from previous 1 week data

This model employs historical stock prices from the past week to predict the KRW/USD exchange rates. In this case, the resulting multiple linear regression model based on backward elimination with significant level 0.05 for all independent variables is given below.

$$\text{KRW/USD} = 1365.20 + 1.732X_2 - 1.034X_4 - 0.993X_5 - 1.088X_8 + 3.714X_9 - 0.338X_{10}$$

where KRW/USD is the Korean Won to US Dollar exchange rate,
X_2 is the stock price of JYP Entertainment
X_4 is the stock price of CJ ENM Co. Ltd
X_5 is the stock price of Studio Dragon
X_8 is the stock price of HYBE Corporation
X_9 is the stock price of Kakao Corporation
X_{10} is the stock price of Amorepacific

Figure 9 compares the daily closing values for the KRW/USD exchange rates and their predicted values using Model 4. Based on the training data, the regression Model 4 has the values for R-squared of 0.768 , adjusted R-squared of 0.764, RMSE of 31.106, and standard error of regression 31.412, as given in Table 2 for Model 3.

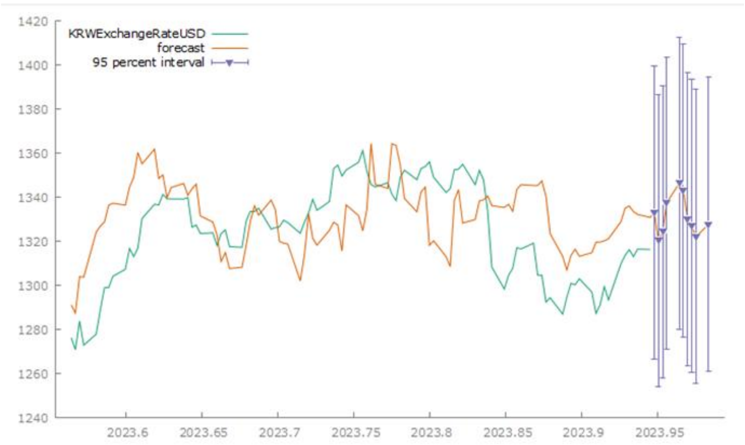


Figure 9: [Model 4] Comparison of actual vs. predicted KRW/USD exchange rate (training set) and the predicted exchange rate of test set with 95% confidence interval.

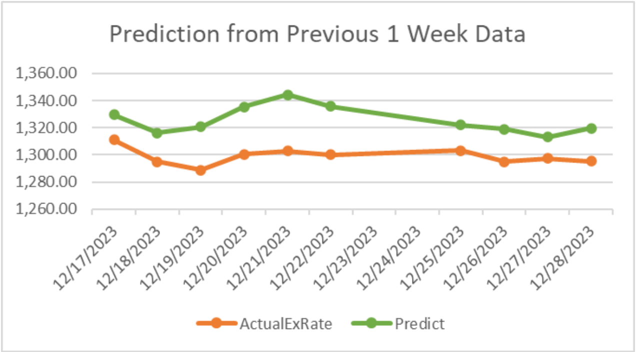


Figure 10: [Model 4] Comparison of actual vs. predicted KRW/USD exchange rate (test data set).

Figure 10 illustrates the future forecast for the exchange rates for the test data using Model 4. The accuracy evaluation of Model 4, when used to forecast exchange rates over a 2-week period (or 10 business days), demonstrates that the model maintains a moderate level of error. The MSE and RMSE values are 778.93 and 27.91, respectively, reflecting the quantitative variance between predicted and actual values. Meanwhile, the MAE stands at 26.69 with a MAPE of 2.06%, indicating an average forecasting error of approximately 2%. These accuracy measures are also shown in Table 3 for Model 4. The trends of the predicted values for Case 4, as illustrated in Figures 9 and 10, align with the actual values at a level considered acceptable for volatile financial data. Table 5 shows the values of VIF for all variables in Model 4, which reflects a multicollinearity issue since the VIF values of the variables X_2 and X_4 are slightly larger than 10. However, these variables are still included in Model 4 to maintain the accuracy of the model.

Table 5: The Variance Inflation Factor (VIF) of each independent variable in Model 4.

Independent Variables in Model 4	**VIF**
X_2 : Stock price of JYP Entertainment	11.693
X_4 : Stock price of CJ ENM Co. Ltd	21.213
X_5 : Stock price of Studio Dragon	8.904
X_8 : Stock price of HYBE	6.824
X_9 : Stock price of Kakao	7.136
X_{10} : Stock price of Amorepacific.	3.614

Discussion

This work considered four regression models. Table 6 shows a summary and goodness-of-fit statistics of these models based on using different training data sets. The comparative analysis of these four predictive models on different test data sets are shown in Table 7, which reveals a distinct correlation between the volume of historical training data and forecasting accuracy. The model, utilizing a 70/30 train-test split, demonstrated limited predictive power, yielding a high Mean Absolute Percentage Error (MAPE) of 11.2148% and a Root Mean Squared Error (RMSE) of 156.7640. This elevated error rate suggests that the model struggled to capture the complex, non-linear volatility of the exchange rate when provided with insufficient historical context. However, forecasting efficiency improved dramatically as the training set was expanded. The 80/20 split reduced the MAPE to 1.86%, while the 90/10 split achieved the lowest variance in terms of squared errors with an MAPE of 1.66%. These results indicate that the regression model benefits significantly from a larger historical corpus, allowing it to better learn the inverse relationships between sectoral stock performance and currency valuation. Based on VIF values of the independent variables shown in Tables 2-5, there are no multicollinearity issues for Models 1 and 2, while there are some multicollinearity issues for Models 3 and 4. Note, however, that the variables with slightly high VIF are still included in Models 3 and 4 to maintain the prediction accuracy of the models.

An important finding of this study is the robust performance of Model 4, which based its predictions on data from the previous one week. Despite lacking the current information on the stock prices, Model 4 achieves a decent degree of accuracy, with a MAPE of 2.05% and an RMSE of 27.91.

This suggests that the influence of entertainment and consumer goods stocks on the KRW/USD exchange rate is immediate and highly path-dependent. The strong performance of Model 4 implies that the relevant market information is embedded in the immediate past where recent price action serves as a sufficient statistic for short-term forecasting.

Table 6: Model summary and goodness-of-fit statistics from training data.

Model	Number of Observations	R Square	Adjusted R Square	Root Mean Squared Error (RMSE)	Standard Error of Regression
1: Train 90%-Test 10%	464	0.682	0.678	33.154	33.407
2: Train 80%-Test 20%	413	0.679	0.674	34.386	34.681
3: Train 70%-Test 30%	361	0.768	0.764	31.106	31.412
4: Model for forecasting from previous 1 week data	506	0.655	0.648	33.025	33.390

Table 7: Predictive performance of models for test data using (Mean Squared Error), RMSE (Root MSE), MAE (Mean Absolute Error) and MAPE (Mean Absolute Percentage Error).

Model	MSE (Mean Squared Error)	RMSE (Root MSE)	MAE (Mean Absolute Error)	MAPE (Mean Absolute Percentage Error)
1: Train 90%-Test 10%	777.18	27.87	21.84	1.66%
2: Train 80%-Test 20%	779.81	27.92	24.39	1.86%
3: Train 70%-Test 30%	24574.95	156.76	147.35	11.22%
4: Model for forecasting from previous 1 week data	**778.93**	**27.91**	**26.69**	**2.05%**

Conclusion

This work employs stock price data from South Korea’s export-oriented industries to serve as highly effective leading indicators for predicting the KRW/USD exchange rate. The empirical evidence demonstrates that when current stock prices are used in the MLR prediction, the best-performing 90/10 split model achieves an MAPE of 1.66%. The model employing the past data approach represented by Model 4 offers a reasonably accurate prediction with an MAPE of 2.05%. By achieving approximately 98% accuracy using the previous week's data, Model 4 highlights the rapid transmission of volatility from the stock market to the currency market. This indicates that for investors and policymakers, monitoring the real-time performance of key "Korean Wave" stocks—such as HYBE and Studio Dragon—provides a reliable, immediate signal for currency hedging strategies, effectively bridging the gap between micro-level corporate performance and macro-level exchange rate dynamics.

Note that, the relationship between stock prices and exchange rates is dynamic and sensitive to recent market regimes. A possible future research direction is therefore to explore rolling-window regression or hybrid machine learning models (e.g., LSTM) that can dynamically update weights as new data becomes available, ensuring high accuracy over longer forecasting horizons.

References

Abdalla, I. S., & Murinde, V. (1997). Exchange rate and stock price interactions in emerging financial markets: Evidence on India, Korea, Pakistan and the Philippines. *Applied Financial Economics*, *7*(1), 25-35.

Aggarwal, R. (1981). Exchange rates and stock prices: A study of the US capital markets under floating exchange rates. *Akron Business and Economic Review*, *12*(3), 7-12.

Branson, W. H. (1983). Macroeconomic determinants of real exchange risk. In R. J. Herring (Ed.), *Managing foreign exchange risk* (pp. 35-74). Cambridge University Press.

Dornbusch, R., & Fischer, S. (1980). Exchange rates and the current account. *The American Economic Review*, *70*(5), 960-971.

Frankel, J. A. (1983). Monetary and portfolio-balance models of the determination of exchange rates. In J. S. Bhandari & B. H. Putnam (Eds.), *Economic interdependence and flexible exchange rates* (pp. 84-115). MIT Press.

Glakiatnarong, N., Sukhodomchoti, J., Srithongkham, K., Lemsen, N., Luivikkai, I., Luivikkai, I., & Tachasaen, T. (2022). Economic factors that determine currency exchange rate between Baht and Yuan. *Journal of KMITL Business School*, *12*(2), 27-40.

Granger, C. W. J., Huang, B. N., & Yang, C. W. (2000). A bivariate causality between stock prices and exchange rates: Evidence from recent Asian flu. *The Quarterly Review of Economics and Finance*, *40*(3), 337-354.

Lee, H. Y. (2023). The time decaying synchronization between the volatility index and KOSPI return. *Business and Economic Research*, *13*(1), 1-14.

Pan, M. S., Fok, R. C. W., & Liu, Y. A. (2007). Dynamic linkages between exchange rates and stock prices: Evidence from East Asian markets. *International Review of Economics & Finance*, *16*(4), 503-520.

Parc, J. (2021). Measuring the impact of Hallyu on Korea’s economy: Setting off on the wrong foot. *Korea’s Economy*, *32*, 27-35.

Park, J. (2023). From cultural export to economic engine: Examining the role of K-Pop in the growth of the South Korean economy. *Open Journal of Business and Management*, *11*(5), 2320-2335.

Srisangngam, K., & Khongsawatkiat, K. (2016). Economic factors determining the exchange rate between Thai Baht and Chinese Yuan. *Journal of Science and Technology*, *28*(1), 26-40.