The Asian Journal of Technology Management Vol. 18 No. 2 (2025): 147-160

Optimization of BRIN's Technology License: Conjoint Experimental Study

Anggun Dwi Puspo Supomo* and Tengku Ezni Balqiah
Faculty of Economics and Business, Universitas Indonesia, Indonesia

Abstract. *Commercialization of research products is a common problem in the product development stage of research institutions where many research products are not utilized to become commercial value. This study aims to analyze the opportunity evaluation by business actors in utilizing technology products from research institutions, especially the National Research and Innovation Agency (BRIN). Conjoint analysis design was carried out to see respondents' assessments of a series of profiles containing theory-based variable manipulations and their influence on decision making according to opportunity evaluation theory. The questionnaire was filled out by 101 individuals who have decision-making authority in the company and analyzed using the Mixed-effect model regression technique. Opportunity attributes (prototype maturity, segment clarity and regulatory hurdless) have a significant effect on the opportunity evaluation to license BRIN's research products. We document the moderating role of individual attributes and environmental dynamism attributes on the influence of opportunity attributes on the opportunity evaluation to license BRIN's research products. This study uses a different approach in analyzing the factors of industry licensing decisions for research products from research institutions by applying opportunity evaluation. This study offers insights for research institutions in utilizing research products for business actors through licensing schemes.*

Keywords: *Commercialization, opportunity evaluation, conjoint analysis, organizational behavior, licensing*

1. Introduction

The commercialization of research products is a complex and uncertain process (Ismail et al., 2015) with significant economic, social, and environmental implications (Kreiling & Bounfour, 2020). Current research focuses on institutional factors such as researcher status (van Holm et al., 2021), the role of leaders (Nasirov et al., 2021), and patent policies (Gu, 2021), as well as the challenges of intellectual property commercialization (Daniel & Alves, 2020). Licensing agreements play a critical role in technology transfer, offering benefits like market expansion and reduced costs (Canalichio, 2018).

Despite these benefits, licensing remains underutilized, especially for research products from Indonesia's National Research and Innovation Agency (BRIN). This reflects wider commercialization barriers shaped by innovation culture, resources, and transfer strategies (Kirchberger & Pohl, 2016). A persistent barrier is the "valley of death," in which early-stage research struggles to progress into marketable innovations (Yu, 2016), despite entrepreneurs willing to license innovations (Wright et al., 2004).

The limited use of licensing for BRIN's research products remains a significant issue in Indonesia, where many research outputs fail to reach commercial application (Maludin et al.,

*Corresponding author. Email: adsupomo@gmail.com
Received: February 3rd, 2025; Revised: September 20th, 2025; Accepted: October 11th, 2025
Doi: http://dx.doi.org/10.12695/ajtm.2025.18.2.5. Print ISSN: 1978-6956; Online ISSN: 2089-791X.

Published by Unit Research and Knowledge- School of Business and Management-Institut Teknologi Bandung
How to cite: *Supomo, A.D.P., and Balqiah, T.E. (2025). Optimization of BRIN's Technology License: Conjoint Experimental Study. The Asian Journal of Technology Management (AJTM), 18(2), 148-161. https://doi.org/10.12695/ajtm.2025.18.2.5*

2021). This challenge is particularly important in the context of national initiatives such as the National Innovation System (SINas) and BRIN's efforts to strengthen industry–research collaboration (Damuri et al., 2018; (Burhani et al., 2021). Much of the technology transfer literature, however, is rooted in Western contexts, while Indonesia's innovation ecosystem is shaped by distinct institutional and cultural dynamics. Regional studies reveal weak industry–research linkages, low awareness of licensing, and limited policy support (Dhewanto & Umam, 2009), underscoring the need for context-specific insights to foster innovation-driven growth (Simatupang et al., 2022).

Existing studies on technology licensing also concentrate on universities in developed economies, leaving limited insights into national R&D agencies in emerging contexts such as Indonesia (Brown et al., 2022; Wright et al., 2008). This gap is critical, as agencies like BRIN face distinct institutional logics, commercialization pathways, and market dynamics compared to universities. Environmental factors such as dynamism and munificence, while central to opportunity evaluation research (Aghaey, 2020), also remain underexplored in licensing studies.

This study extends Brown et al.'s (2022) opportunity–individual model with environmental dimensions from Aghaey (2020) to examine factors influencing industry decisions to license BRIN's research products. It also explores how individual and environmental conditions moderate these decisions, thereby advancing licensing scholarships in emerging economies and offering practical guidance for policymakers and research institutions.

2. Literature Review/Hypotheses Development

2.1 Theoritical background

Opportunity evaluation enables entrepreneurs to assess the feasibility and profitability of business opportunities (McMullen & Shepherd, 2006; Aghaey, 2020). Brown et al. (2022) identified three technological attributes: prototype maturity, segment clarity, and regulatory hurdles—while also emphasizing the role of individual characteristics such as technology-specific knowledge and active search for licensing. Aghaey (2020) further highlighted environmental conditions, particularly dynamism and munificence, as influential factors.

Licensing is central to research commercialization, allowing firms to lease intangible assets (Canalichio, 2018; Wild & Wild, 2020). It is often applied to early-stage discoveries requiring further development with researcher involvement (Thursby et al., 2001). For entrepreneurs, licensing provides credibility, market expansion, and access to intangible assets (Canalichio, 2018), making it a vital bridge between research institutions and industry.

2.1.1 Technology Attributes

2.1.1.1. Prototype Maturity

Reflects readiness from proof of concept to marketable prototypes; higher maturity accelerates commercialization, while early-stage technologies face patenting and scale-up risks (Brown et al., 2022; Thursby et al., 2001).

2.1.1.2. Segment Clarity

Indicates how clearly target markets are identified, (Brown et al., 2022), reducing uncertainty through early adopters (Rogers, 2003) and easing positioning against competitors (Shane, 2001).

2.1.1.3. Regulatory Hurdles

Encompasses rules that affect commercialization costs, timelines, and compliance (Brown et al., 2022). Regulations add risks (Sisodia et al., 2016) uncertainty can sometimes stimulate adoption (Frederiks et al., 2024).

2.2.1 Individual Attributes

Opportunity evaluation is shaped by entrepreneurs' technology-specific knowledge and active search, both of which guide feasibility assessments and market potential in licensing decisions (Brown et al., 2022)

2.3.1 Environmental Condition

External factors also shape licensing decisions (Aghaey, 2020). Dynamism captures uncertainty from rapid changes, while munificence reflects resource abundance and growth potential. Both conditions moderate opportunity evaluation (Chen et al., 2017)

2.2 Hyphoteses Development

2.2.1 Direct Influence of Opportunity Attributes

Entrepreneurs evaluate technology based on prototype maturity, segment clarity, and regulatory hurdles when considering licensing opportunities.

The academically complete prototype still needs development to transform laboratory-scale discoveries into commercial scales (Agrawal, 2006). Brown et al. (2022) found that high prototype maturity positively impacts licensing likelihood. Thus, the study hypothesizes:

H1: Prototype maturity positively affects entrepreneurs' likelihood of licensing BRIN's research technology products.

Segment clarity reduces uncertainty by identifying clear early adopters, making commercialization more predictable (Rogers, 2003). Brown et al. (2022) demonstrated that higher segment clarity increases licensing probability. The hypothesis proposed is:

H2: Segment clarity positively affects entrepreneurs' likelihood of licensing BRIN's research technology products.

Regulatory hurdles are perceived as costs (Lee & Lee, 2019), increasing uncertainty and reducing licensing attractiveness (Mcmullen et al., 2016). Brown et al. (2022) suggest that stringent regulations negatively impact licensing decisions. The study hypothesizes:

H3: Regulatory hurdles positively affect entrepreneurs' likelihood of licensing BRIN's research technology products.

2.3.1 The Moderating Role of Individual Attributes

Knowledge of technology has the potential to increase user involvement in making personal decisions in increasingly diverse domains (Cegarra-Navarro et al., 2014). Technology-specific knowledge such as knowledge related to systems, settings and functional features play a crucial role in technology transfer by aiding prototype development and reducing uncertainty in commercialization (Agrawal, 2006). Entrepreneurs with high technology-specific knowledge are less tolerant of immature prototypes, as their expertise enables them to develop the technology into a commercial product. However, Brown et al. (2022) found no significant interaction between technology-specific knowledge and prototype maturity. This study proposes:

H4a: Technology-specific knowledge weakens the positive effect of prototype maturity on licensing decisions.

Entrepreneurs use their knowledge to assess market needs (Erickson et al., 1990; Brown et al., 2022) and determine the feasibility of technologies (Bennett, 2002). Brown et al., (2022) explained that they prefer clear market segments but can evaluate uncertain opportunities if they possess sufficient knowledge. Thus, the study hypothesizes:

H4b: Technology-specific knowledge weakens the positive effect of segment clarity on licensing decisions.

Regulatory hurdles are generally seen as barriers, but entrepreneurs with high technology-specific knowledge can better estimate compliance costs (Sandström et al., 2018). They value low regulatory hurdles more than those with less knowledge (Brown et.al., 2022). The study hypothesizes:

H4c: Technology-specific knowledge strengthens the negative effect of regulatory hurdles on licensing decisions.

Entrepreneurs prefer mature prototypes due to lower commercialization uncertainty (Agrawal, 2006). However, those with a high

level of active search are more likely to recognize the commercial potential of less mature prototypes, reducing doubts about their viability (Brown et al., 2022). Thus, the study hypothesizes:
H5a: Active search weakens the positive effect of prototype maturity on licensing decisions.

Active search also influences how entrepreneurs assess segment clarity. Those who actively seek technology solutions are more flexible in exploring opportunities with unclear market segments, as they can identify potential customers and market needs (Markman et al., 2008; Brown et al., 2022). This leads to the hypothesis:
H5b: Active search weakens the positive effect of segment clarity on licensing decisions.

Regulatory hurdles deter entrepreneurs due to commercialization constraints. However, those engaged in active search understand that research-based technologies often face high regulatory burdens (Tang et al., 2012). They highly value technologies with low regulatory barriers due to their rarity (Brown et al., 2022). Therefore, the study proposes:
H5c: Active search strengthens the negative effect of regulatory hurdles on licensing decisions.

2.4.1The moderating role of environmental attributes
Dynamic markets are unpredictable, as current competitive analyses may not hold in the future due to innovations and may be a critical factor in determining the 'right' innovations for the future market (Gottinger, 2016). Market evolution often requires radical technological innovation to stay competitive and avoid disruption (Oehler, 2021). High industry dynamism creates opportunities for new product development, emerging market segments, and evolving regulations.

Entrepreneurs in dynamic industries may actively seek mature prototypes to address new market needs. Similarly, clear market segments become even more attractive in fast-changing environments, where entrepreneurs prefer predictable demand. However, increasing regulatory complexity may add further hurdles, impacting opportunity evaluation.

Thus, the study proposes:
H6a: Dynamism strengthens the positive effect of prototype maturity on licensing decisions.
H6b: Dynamism strengthens the positive effect of segment clarity on licensing decisions.
H6c: Dynamism strengthens the negative effect of regulatory hurdles on licensing decisions.

Companies in resource-rich environments can better adapt to external threats (Nielsen & Nielsen, 2013), while resource-scarce environments face intense competition and limited profitable opportunities (Covin & Slevin, 1989). Abundant resources accelerate prototype maturation, making technology commercialization more efficient.

In high-munificence markets, consumers have more alternatives, increasing competition and blurring market segmentation as differences between segments shrink. Additionally, resource-rich industries tend to experience regulatory expansion to support growth.

Based on these insights, the study proposes:
H7a: Munificence strengthens the positive effect of prototype maturity on licensing decisions.
H7b: Munificence weakens the positive effect of segment clarity on licensing decisions.
H7c: Munificence weakens the negative effect of regulatory hurdles on licensing decisions.

Figure 1 presents the conceptual model, showing the direct effects of opportunity attributes on licensing decisions and the moderating roles of individual and environmental attributes.

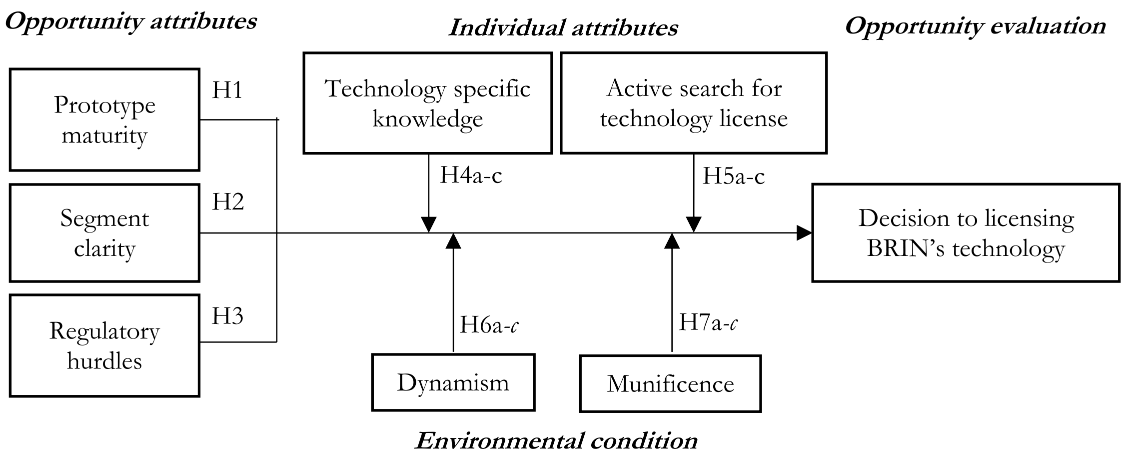

Figure 1.
Conceptual framework of opportunity evaluation for licensing BRIN's technology. Prototype maturity (+), segment clarity (+), and regulatory hurdles (–) directly influence licensing likelihood, moderated by individual attributes (technology-specific knowledge, active search) and environmental attributes (dynamism, munificence)
Source: Author

3. Methodology

3.1 Research concept
This study adopts Brown et al.'s (2022) framework to analyze factors influencing industry decisions to license BRIN's research products. It examines opportunity and individual attributes, along with environmental conditions (dynamism and munificence) from Aghaey (2020) to assess their role in facilitating or hindering opportunity evaluation.

A metric conjoint analysis is applied, assuming no correlation between attributes (Aghaey, 2020). The study follows Brown et al.'s (2022) full orthogonal factorial design with three attributes (prototype maturity, segment clarity, and regulatory hurdles) each varying at two levels (high and low), generating eight decision profiles. Two additional profiles test respondent consistency and are analyzed separately. Profiles are presented randomly to prevent order effect bias, ensuring a robust assessment of industry licensing decisions for BRIN's research innovations.

Conjoint analysis is employed because it systematically captures how decision-makers trade off among competing attributes in complex licensing choices, assuming zero correlation between attributes (orthogonality) (Shepherd et al., 2013). Aghaey (2020) applied conjoint experiments to explore decision policies of corporate and independent entrepreneurs, while Haynie et al. (2013) demonstrated its strength in quantifying trade-offs and identifying key drivers of opportunity pursuit. Building on this literature, our study applies conjoint analysis to the underexplored context of a national R&D agency in an emerging economy.

3.2 Participants
This study surveyed strategic decision-makers from BRIN's license partners, prospective partners, and incubation partners using judgmental sampling. While this ensured respondents' exposure to technology commercialization and licensing, it may bias the sample toward BRIN-adjacent firms and inflate familiarity with its processes; future research should therefore control for BRIN familiarity or prior licensing experience. Data were collected through a structured questionnaire distributed via WhatsApp and email, yielding 101 valid responses from 241 invitations. This sample meets the minimum threshold for conjoint analysis (Cattin & Wittink, 1982) and provides sufficient power for estimating mixed-effects regression

models given the 808 decision profiles. The sample size also aligns with prior conjoint studies (Haynie et al., 2009; Aghaey, 2020; Brown et al., 2022).

3.3 Measurement

This study uses conjoint experiments to assess how changes in variables affect belief formation and licensing intentions (Wood et al., 2016). The questionnaire includes instructions, technology descriptions, attribute definitions, conjoint profiles, and demographics. A wording test was conducted with 10 respondents, and a pre-test with 30 respondents ensured validity and reliability. Descriptive analysis examined distribution characteristics (Cooper & Schindler, 2014). Respondents evaluated individual and environmental attributes before assessing a series of conjoint profiles. Due to potential correlation, the intra-class correlation coefficient (ICC) was used to test data independence (Aghaey, 2020). Reliability and validity were assessed using the goodness of fit of the estimated model (Malhotra et al., 2016). The study employs mixed-effects regression with maximum likelihood estimation, where intercepts represent willingness to pursue opportunities beyond opportunity attributes (Shepherd et al., 2013). The analysis includes five models at 2 levels:

Level-1 model: Tests significance of three opportunity attributes.

Level-2 model: Examines cross-level interactions between level-1 (within-individual) and level-2 (between-individual).

4. Findings and Discussion

4.1 Sample Profile

Table 1 presents the demographics of 101 respondents: 79.2% male and 20.8% female. Most (50.5%) held undergraduate degrees, indicating generally relevant educational backgrounds. Similarly, 50.5% had over 10 years of work experience, reflecting substantial professional tenure. In terms of roles, 46% were managers and 40% directors, showing that individuals in leadership positions were the most accessible for this study.

Table 1.
Demographic Characteristics of The Sample

Variables	Number	%
Gender		
Male	80	79.21%
Female	21	20.79%
Education		
High school	4	3.96%
Undergraduate	51	50.50%
Postgraduate	37	36.63%
Doctoral	9	8.91%
Experience in industry		
1-3 years	10	9.90%
3-5 years	13	12.87%
5-10 years	27	26.73%
> 10 years	51	50.50%
Position level		
Manager	47	46.53%
Director	40	39.60%
Commisioner	3	2.97%
Owner	11	10.89%

4.2 Intra-Class Correlation Coefficient (ICC) Analysis

The ICC value assuming independence of regression responses is used to determine the need to conduct a multilevel analysis of the data in this study. According to Aghaey (2020), an ICC value above 0.1 suggests a violation of response independence, requiring consideration of correlations within individuals to ensure proper analysis. The table below presents an unconditional (intercept-only) model, where the ICC value exceeds the standard 0.1 threshold. Therefore, there is a need for a multilevel examination of the dependent construct of this study, namely the evaluation of the probability of a decision to license a research product.

Table 2.
Unconditional (intercept-only) Model

Variance	***Sample***
varians residual level-1, $\boldsymbol{\tau_{00}}$	2.79 (0.14)
varians residual level-2, $\boldsymbol{\sigma^2}$	0.86 (0.17)
intra-class correlation coefficient	0.24

$p < 0.05$

4.3 Test of Reliability and Validity Values of Conjoint Analysis

According to Malhotra et al. (2016), the reliability and validity of conjoint analysis can be assessed through goodness-of-fit and test-retest reliability. The estimated model yielded an R^2 of 0.267, indicating that the independent variables explain 26.7% of the variance in licensing decisions. Although acceptable, this value falls below the 0.60 threshold, and the study is further limited by the small sample size (101 responses). This suggests that additional factors such as organizational culture, prior commercialization experience, and market conditions may also shape licensing decisions. The findings should be viewed as preliminary and future studies with larger and more diverse samples are recommended. To assess test-retest reliability, replicated profiles (3/9 and 6/10) produced $\Delta R^2 = 0.018$. This findings confirm that the model demonstrates good stability.

4.4 Hypothesis Testing

Hypothesis testing is used to examine the relationships between constructs and evaluate the impact of different variables. The main effect test is performed on level-1 data, which represents within-individual effects (predictors and controls). Meanwhile, the moderation effect test is applied to both level-1 (within-individual effects) and level-2 data (between-individual effects), incorporating predictors, controls, and moderators.

We report the estimated coefficients with 95% confidence intervals for all tested paths (see Table 3). Significant effects are denoted at $p < 0.05$. The intercept value represents an entrepreneur's inclination to pursue opportunities, independent of the three opportunity attributes (Aghaey, 2020).

In Model 1, the parameter coefficient (β) indicates the direction of the predictor's effect on the dependent variable, based on whether the value is positive or negative. Meanwhile, in Models 2, 3, 4, and 5, the parameter coefficient (β) reflects the moderating variable's role in shaping the relationship between the predictor and the dependent variable, also assessed by its positive or negative value.

Table 3.
Mix-Effects Regression Results for Licensing Decisions

Predictor	Coefficient (β)	Error	95% CI	Hypotheses Result
Level 1 Within individual effects				
Model 1				
Prototype Maturity	1.176 *	0.111	[0.958, 1.394]	H1 Supported
Segment Clarity	1.536 *	0.111	[1.318, 1.754]	H2 Supported
Regulatory Hurdless	-0.417 *	0.111	[-0.635, -0.199]	H3 Supported
Intercept	2.024 *	0.270	[1.495, 2.553]	
Level 2 Within-between effects				
Model 2				
Technology Spesific Knowledge X				
Prototype Maturity	-0.341	0.225	[-0.782, 0.100]	H4a Not Supported
Segment Clarity	-0.145	0.220	[-0.576, 0.286]	H4b Not Supported
Regulatory Hurdless	-0.508 *	0.220	[-0.939, -0.077]	H4c Supported
Intercept	2.332 *	0.294	[1.756, 2.098]	
Model 3				
Technology Active Search X				
Prototype Maturity	-0.698 *	0.224	[-1.138, -0.258]	H5a Supported
Segment Clarity	-0.205	0.220	[-0.636, 0.226]	H5b Not Supported
Regulatory Hurdless	-0.058	0.220	[-0.489, 0.373]	H5c Not Supported
Intercept	2.426 *	0.288	[1.862, 2.990]	
Model 4				
Environmental Dynamism X				
Prototype Maturity	-0.870 *	0.224	[-1.305, -0.435]	H6a Not Supported
Segment Clarity	0.432 *	0.220	[0.005, 0.859]	H6b Supported
Regulatory Hurdless	0.183	0.220	[-0.248, 0.614]	H6c Not Supported
Intercept	2.599 *	0.300	[2.011, 3.187]	
Model 5				
Industry Munificence X				
Prototype Maturity	-0.597 *	0.222	[-1.033, -0.161]	H7a Not Supported
Segment Clarity	-0.015	0.218	[-0.442, 0.412]	H7b Not Supported
Regulatory Hurdless	-0.318	0.218	[-0.745, 0.109]	H7c Not Supported
Intercept	2.403 *	0.288	[1.839, 2.967]	

** $p < 0.05$, Decision level N = 808; Individual level N = 101*

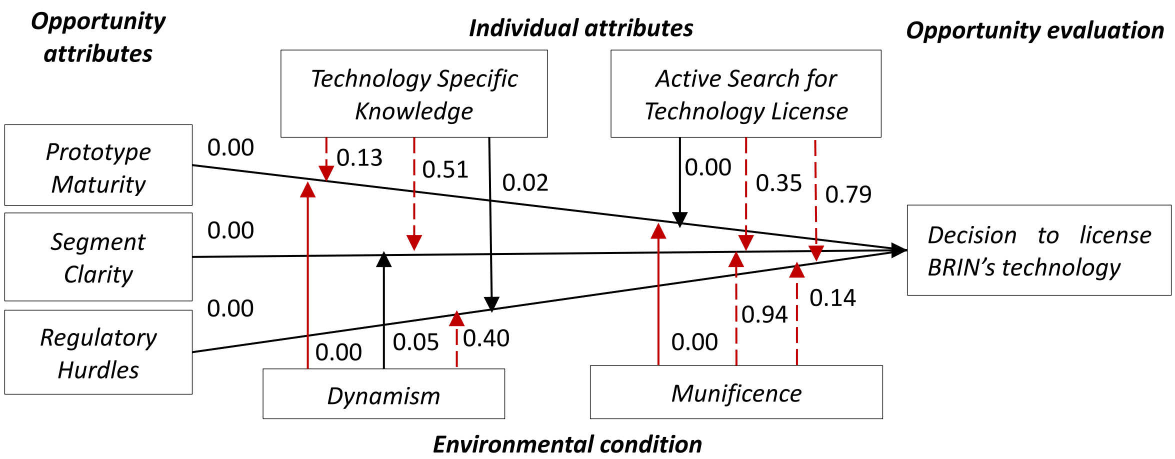

Figure 2.
Model Analysis Result

The coefficient values presented in Figure 2 indicate the significance levels of the tested relationships. A hypothesis is supported if $p < 0.05$, with the sign of β showing the direction of the effect. In Model 1, β indicates direct effects, while in Models 2–5 it reflects moderating effects.

4.5 Discussion

Hypotheses 1, 2, and 3 are supported by Model 1, which shows a positive and significant intercept value (β = 2.024, $p < 0.05$), indicating that entrepreneurs are inclined to pursue opportunities to license research products. The coefficient for prototype maturity is positive and significant (β = 1.176, $p < 0.05$), supporting Hypothesis 1. This confirms that higher prototype maturity positively influences entrepreneurs' motivation to license BRIN's research products, aligning with Brown et al. (2022). Mature prototypes present lower commercialization risks, making them more attractive for licensing.

Similarly, the coefficient for segment clarity is positive and significant (β = 1.536, $p < 0.05$), supporting Hypothesis 2. This suggests that clearer market segmentation enhances entrepreneurs' motivation to license BRIN's research products, consistent with Brown et al. (2022). When market clarity is high, uncertainty in commercialization decreases, increasing the likelihood of product licensing.

Conversely, the coefficient for regulatory hurdles is negative and significant (β = -0.417, $p < 0.05$), supporting Hypothesis 3. This indicates that higher regulatory burdens reduce entrepreneurs' motivation to license BRIN's research products, consistent with Brown et al. (2022). Regulations pose risks and require additional costs, time, and resources, making highly regulated research products less attractive for adoption.

Hypotheses 4a, 4b, and 4c are tested in Model 2, where the intercept value is positive and significant (β = 2.332, $p < 0.05$), indicating that entrepreneurs are motivated to pursue licensing opportunities for research products.

The moderation effect of technology-specific knowledge on prototype maturity is negative and not significant (β = -0.341, $p > 0.05$), meaning Hypothesis 4a is not supported. Similarly, its effect on segment clarity is also negative and not significant (β = -0.145, $p > 0.05$), failing to support Hypothesis 4b. The high variability in the data may contribute to these not significant results, despite the effect direction aligning with previous research.

However, the moderation effect of technology-specific knowledge on regulatory hurdles is negative and significant (β = -0.508, $p < 0.05$), supporting Hypothesis 4c. This suggests that technology-specific knowledge amplifies the negative impact of regulatory hurdles on entrepreneurs' likelihood of licensing BRIN's research products. Consistent with Brown et al. (2022), entrepreneurs with higher technology-specific knowledge are more cautious when evaluating products with lower regulatory burdens. They are also more inclined to license products with high regulatory hurdles, as their expertise allows them to navigate complex regulations more effectively.

Hypotheses 5a, 5b, and 5c are tested in Model 3, where the intercept value is positive and significant ($\beta = 2.426$, $p < 0.05$), indicating that entrepreneurs are motivated to pursue opportunities to license research products.

The moderation effect of active search on prototype maturity is negative and significant ($\beta = -0.698$, $p < 0.05$), supporting Hypothesis 5a. This suggests that active search weakens the positive impact of prototype maturity on the likelihood of entrepreneurs licensing BRIN's research technology products. This aligns with prior studies (Brown et al., 2022), which found that active search reduces the influence of prototype maturity. Entrepreneurs with a high level of active search tend to engage more deeply with research products, making them more open to licensing technologies with lower prototype maturity, as they can better assess opportunities.

However, the moderation effect of active search on segment clarity is negative but not significant ($\beta = -0.205$, $p > 0.05$), meaning Hypothesis 5b is not supported. Similarly, its effect on regulatory hurdles is also negative but not significant ($\beta = -0.058$, $p > 0.05$), failing to support Hypothesis 5c. The high variability in the data may have influenced these results, even though the effect direction remains consistent with previous findings.

Hypotheses 6a, 6b, and 6c are tested in Model 4, where the intercept value is positive and significant ($\beta = 2.599$, $p < 0.05$), indicating that entrepreneurs are motivated to pursue opportunities to license research products.

The moderation effect of environmental dynamism on prototype maturity is negative and significant ($\beta = -0.870$, $p < 0.05$), does not support Hypothesis 6a. Environmental dynamism, which reflects rapid changes in consumer preferences, technology, and competition, does not encourage entrepreneurs to pursue opportunities for mature prototypes. This suggests that in highly dynamic environments, entrepreneurs may prioritize adaptability over technological maturity.

However, the moderation effect of environmental dynamism on segment clarity is positive and significant at the 0.05 level ($\beta = 0.432$, $p < 0.05$), supporting Hypothesis 6b. This aligns with Aghaey (2020), who found that environmental conditions positively influence how opportunity attributes impact entrepreneurs' likelihood of licensing technology products. In dynamic environments, entrepreneurs are more inclined to pursue research products with well-defined market segments, as clear segmentation reduces uncertainty.

The moderation effect of environmental dynamism on regulatory hurdles is positive but not significant ($\beta = 0.183$, $p > 0.05$), failing to support Hypothesis 6c. This may be because companies in highly dynamic industries tend to have flexible structures, making it easier to navigate regulatory challenges (Eisenhardt & Martin, 2000). Consequently, regulatory hurdles have a weaker negative impact on technology licensing decisions in such environments.

Hypotheses 7a, 7b, and 7c are tested in Model 5, where the intercept value is positive and significant ($\beta = 2.403$, $p < 0.05$), indicating that entrepreneurs are motivated to pursue opportunities to license research products.

The moderation effect of industry munificence on prototype maturity is negative and significant ($\beta = -0.597$, $p < 0.05$), which does not support Hypothesis 7a. Industry munificence, reflecting abundant resources, allows companies to be more flexible in responding to challenges (Nielsen & Nielsen, 2013). However, according to Usman et al. (2021), resource abundance reduces the urgency for companies to pursue opportunities, as they feel less pressure to act immediately.

The moderation effect of industry munificence on segment clarity is negative and not significant ($\beta = -0.015$, $p > 0.05$), not supporting Hypothesis 7b. With abundant resources, entrepreneurs can afford to wait for research products with clearer market segments, rather than opting to license earlier-stage technologies. The moderation effect of industry munificence on regulatory hurdles is also negative and not significant ($\beta = -0.318$, $p > 0.05$), failing to support Hypothesis 7c. When resources are plentiful, entrepreneurs experience less pressure from regulatory complexities, reducing their concern about regulatory barriers in the adoption of research products.

The findings sharpen our understanding of opportunity evaluation in Indonesia's research commercialization context. Prototype maturity ($\beta = 1.176$, $p < 0.05$) and segment clarity ($\beta = 1.536$, $p < 0.05$) emerged as the strongest drivers of licensing likelihood. While technology-specific knowledge and active search moderated some effects, several hypothesized interactions (e.g., knowledge × prototype maturity; dynamism × prototype maturity) were unsupported, suggesting that contextual factors in Indonesia limit the predictive power of individual and environmental attributes. Diverging from Western-focused studies, this evidence shows that industry partners in emerging economies prioritize tangible technology readiness and market clarity over abstract environmental conditions. For policy, advancing technologies to higher TRL levels, embedding systematic market validation, and streamlining regulatory processes, especially in dynamic sectors are critical. Although some hypotheses were not supported, likely due to institutional constraints and heterogeneous markets, the moderating role of environmental conditions indicates that resource-constrained firms are more motivated to adopt BRIN's innovations. These findings underscore the need for context-sensitive interventions: improving prototype readiness, strengthening researcher–industry collaboration, clarifying market segmentation, and providing regulatory support to accelerate commercialization.

5. Conclusion

The opportunity attributes (prototype maturity, segment clarity, and regulatory hurdles) directly and significantly influence entrepreneurs' evaluations of licensing BRIN's research products. Among individual attributes, technology-specific knowledge amplifies the negative effect of regulatory hurdles, while active search weakens reliance on prototype maturity, encouraging consideration of less mature technologies. Environmental dynamism strengthens the role of segment clarity, but munificence shows no significant moderating effect. Overall, licensing decisions are driven more by individual knowledge and search behavior than by external resources, highlighting the need for BRIN and policymakers to adapt commercialization strategies accordingly..

5.1 Practical implications

Based on our findings, we recommend that BRIN and policymakers prioritize advancing research outputs to higher prototype maturity, supported by systematic market segmentation and validation to align with industry demand. This should be complemented by training programs to enhance technology-specific knowledge, streamlined regulatory processes to reduce uncertainty, and stronger researcher–industry partnerships for market-oriented innovations. Such measures can help overcome licensing barriers, foster a dynamic innovation ecosystem, and strengthen Indonesia's long-term competitiveness.

5.2 *Limitation and future research directions*

While conjoint analysis and mixed-effects regression capture individual-level variation in licensing preferences, this study is limited by a small sample (101 responses), moderate model fit ($R^2 = 0.267$), and using individual decisions as proxies for organizations. The fixed attribute set focus on key parameters, and semantic-to-Likert scale conversion may reduce explanatory power and measurement validity. Respondents were also drawn from BRIN-adjacent firms, potentially inflating familiarity and limiting external validity. Future research should use larger, more diverse samples, including multiple respondents per organization, expand attributes, and control for prior BRIN familiarity or licensing experience.

Declarations

Acknowledgment

The first author would like to thank the Indonesia Endowment Fund for Education Agency (LPDP) from the Ministry of Finance Republic Indonesia for granting the scholarship and supporting this study.

The authors would like to thanks the National Research and Innovation Agency for their support in this study.

The authors would like to express their gratitude to Prof. Dr. Ir. Tengku Ezni Balqiah, M.E., M.H. for her valuable comments of the draft version of this paper and his inspiration to further research study.

Author Contribution

Author 1: conceptualization, writing original draft, data curation, formal analysis, investigation, methodology. Author 2: review and editing, writing review and editing, supervision, validation, visualization.

Financial Disclosure

This research received funding support from LPDP which is included in the education scholarship component.

Conflict of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

References

Aghaey, A. (2020). *Differences in opportunity evaluation between corporate and independent entrepreneurs.*

Agrawal, A. (2006). Engaging the inventor: Exploring licensing strategies for university inventions and the role of latent knowledge. *Strategic Management Journal,* 27(1), 63–79.

Bennett, B. E. N. (2002). *Market scoping: methods to help people understand their marketing environment*. 71–77.

Brown, A. R., Wood, M. S., & Scheaf, D. J. (2022). Discovery sells, but who's buying? An empirical investigation of entrepreneurs' technology license decisions. *Journal of Business Research*, 144(March 2021), 403–415.

Burhani, A. N., Mulyani, L., & Pamungkas, C. (2021). *The National Research and Innovation BRIN; A new Arrangement for Research in Indonesia.* Heng Mui Keng Terrace, Singapore: ISEAS Publishing.

Canalichio, P. (2018). *Making the Decision to License.* Expand, Grow, Thrive, 173–215.

Cattin, P., & Wittink, D. R. (1982). Commercial Use of Conjoint Analysis: A Survey. *Journal of Marketing*, 46(3), 44.

Cegarra-Navarro, J. G., Garcia-Perez, A., & Moreno-Cegarra, J. L. (2014). Technology knowledge and governance: Empowering citizen engagement and participation. *Government Information Quarterly,* 31(4), 660–668.

Chen, H., Zeng, S., Lin, H., & Ma, H. (2017). Munificence, Dynamism, and Complexity: How Industry Context Drives Corporate Sustainability. *Business Strategy and the Environment*, 125-141.

Cooper, D. R., & Schindler, P. S. (2014). *Business Research Methods.* McGraw-Hill Education.

Damuri, Y. R., Aswicahyono, H., & Cristian, D. (2018). Chapter 4: Innovation policy in Indonesia. *In M. Ambashi, Innovation Policy in ASEAN* (pp. 96-127). ERIA.

Daniel, A. D., & Alves, L. (2020). University-industry technology transfer: the commercialization of university's patents. *Knowledge Management Research and Practice,* 18(3), 276–296.

Dhewanto, W., & Umam, K. K. (2009). Technology commercialization in a developing country: Current Condition and Its Challenge in Indonesia. *The Asian Journal of Technology Management*, 1-7.

Eisenhardt, K. M., & Martin, J. A. (2000). Dynamic Capabilities: What Are They? *Strategic Management Journal,* 21(10), 1105–1121.

Frederiks, A. J., Costa, S., Hulst, B., & Groen, A. J. (2024). The early bird catches the worm: The role of regulatory uncertainty in early adoption of blockchain's cryptocurrency by fintech ventures. *Journal of Small Business Management,* 62(2), 790–823.

Gottinger, H. W. (2016). Innovation, Dynamics of Competition and Market Dynamics`. *Archives of Business Research*, 4(1).

Gu, J. (2021). Effects of patent policy on outputs and commercialization of academic patents in china: A spatial difference-in-differences analysis. *Sustainability (Switzerland),* 13(23).

Haynie, J. M., Shepherd, D. A., & McMullen, J. S. (2009). An Opportunity for Me? The Role of Resources in Opportunity Evaluation Decisions. *Journal of Management Studies*, 337-361.

Ismail, N., Nor, M. J. M., & Sidek, S. (2015). A Framework for a Successful Research Products Commercialisation: A Case of Malaysian Academic Researchers. *Procedia - Social and Behavioral Sciences,* 195, 283–292.

Kirchberger, M. A., & Pohl, L. (2016). Technology commercialization: a literature review of success factors and antecedents across different contexts. *Journal of Technology Transfer,* 41(5), 1077–1112.

Kreiling, L., & Bounfour, A. (2020). A practice-based maturity model for holistic TTO performance management: development and initial use. *Journal of Technology Transfer,* 45(6), 1718–1747.

Lee, R., & Lee, Y. il. (2019). The role of nation brand in attracting foreign direct investments: a case study of Korea. *International Marketing Review,* 38(1), 124–140.

Malhotra, N. K., & Dash, S. (2016*). Marketing Research; An Applied Orientation (Seventh Ed).* Pearson India Education Services Pvt. Ltd.

Maludin, S., Syarief, R., Rifin, A., & Rochman, N. T. (2021). Reassembling technology transfer in Indonesia. *International Journal of the Analytic Hierarchy Process*, 5(2), 437-457.

Mcmullen, J. S., Wood, M. S., & Kier, A. S. (2016). An Embedded Agency Approach To Entrepreneurship Public Policy: Managerial Position And Politics In New Venture Location Decisions. *Academy of Management Perspectives,* 30(3), 222–246.

Nasirov, S., Li, Q. C., & Kor, Y. Y. (2021). Converting technological inventions into new products: The role of CEO human capital. *Journal of Product Innovation Management,* 38(5), 522–547. https://doi.org/10.1111/jpim.12601

Nielsen, B. B., & Nielsen, S. (2013). Top management team nationality diversity and firm performance: A multilevel study. *Strategic Management Journal,* 34(3), 373–382.

Oehler, L. (2021). *Technological Change and the Decomposition of Innovation Choices and Consequences for Latecomer Firm Upgrading.* Copenhagen Business School.

Rogers, E. M. (2003). *Diffusion of Innovations, 5th Edition*. Free Press.

Sandström, C., Wennberg, K., Wallin, M. W., & Zherlygina, Y. (2018). Public policy for academic entrepreneurship initiatives: a review and critical discussion. *Journal of Technology Transfer,* 43(5), 1232–1256.

Shane, S. (2001). Technological Opportunities and New Firm Creation. *Management Science*, 47(2), 205-220.

Shepherd, D. A., Patzelt, H., & Baron, R. A. (2013). I care about nature, but...": Disengaging values in assessing opportunities that cause harm. *Academy of Management Journal,* 56(5), 1251-1273.

Simatupang, T. M., Silalahi, F. T., Okdinawati, L., Nandini, W., & Fajarani, P. F. (2022). Indonesia's innovation policies: Evolution and institutional structure. *STI Policy and Management,* 87-96.

Sisodia, G. S., Soares, I., & Ferreira, P. (2016). Modeling business risk: The effect of regulatory revision on renewable energy investment - The Iberian case. Renewable Energy, 303-313Tang, J., Kacmar, K. M. M., & Busenitz, L. (2012). Entrepreneurial alertness in the pursuit of new opportunities. *Journal of Business Venturing,* 27(1), 77–94.

Thursby, J. G., Jensen, R., & Thursby, M. C. (2001). Objectives, Characteristics and Outcomes of University Licensing: A Survey of Major U.S. Universities. *The Journal of Technology Transfer*, 59–72.

Usman, B., Sheikh, S. M., Yousaf, S. U., & Akram, M. W. (2021). Impact of Industrial Munificence , Industry Dynamism and Asset Structureon the Firm Leverage. *Elementary Education Online,* 20(4), 188–198.

Van Holm, E. J., Jung, H., & Welch, E. W. (2021). The impacts of foreignness and cultural distance on commercialization of patents. In *Journal of Technology Transfer* (Vol. 46, Issue 1). Springer US.

Wild, John J; Wild, K. L. (2020). *International Business: The Challenges of Globalization, eBook, Global Edition (Ninth Edit).* Pearson Education Limited.

Wood, M. S., Bylund, P., & Bradley, S. (2016). The influence of tax and regulatory policies on entrepreneurs' opportunity evaluation decisions. *Management Decision*, 54(5), 1160–1182.

Wright, M., Birley, S., & Mosey, S. (2004). Entrepreneurship and University Technology Transfer. *Journal of Technology Transfer*, 29, 235–246.

Wright, M., Clarysse, B., Lockett, A., & Knockaert, M. (2008). Mid-range universities' linkages with industry: Knowledge types and the role of intermediaries. *Research Policy*, 1205-1223.

Yu, H. W. H. (2016). Bridging the translational gap: Collaborative drug development and dispelling the stigma of commercialization. *Drug Discovery Today,* 21(2), 299–305.