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"A TIME-VARYING ECOSYSTEM MODEL OF TECHNOLOGY READINESS, INTEREST DEVELOPMENT, AND CAREER ALIGNMENT IN CREATIVE INDUSTRIES"

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Abstract:

This study investigates the limitations of existing static models in explaining career development within digitally mediated creative industries. In the contemporary creative economy, career trajectories are increasingly shaped by platform-driven ecosystems, iterative participation, and continuous technological adaptation. However, dominant frameworks such as the Technology Readiness Index (TRI) and the Unified Theory of Acceptance and Use of Technology (UTAUT) remain grounded in cross-sectional and temporally stable assumptions, creating theoretical misalignment in explaining dynamic career formation. To address this gap, this study develops and empirically validates the Time-Varying Ecosystem Model of Technology Readiness, Interest Development, and Career Alignment (TVEM-TRICA). A longitudinal quantitative research design involving three waves of data collection (T1–T3) was employed. Data were analysed using cross-lagged panel modelling, latent growth modelling, and structural equation modelling (SEM) to capture reciprocal and time-dependent relationships among constructs. The findings reveal a dynamic reconfiguration of causal influence, where technology readiness significantly shapes early-stage interest ($\beta = 0.41$, $p < 0.001$) but diminishes over time, while interest progressively becomes the dominant predictor of career alignment ($\beta = 0.47$, $p < 0.001$). UTAUT constructs demonstrate declining influence across temporal stages, whereas ecosystem factors significantly moderate and mediate key relationships. This study contributes theoretically by shifting the analytical paradigm from static variance explanation to time-dependent process modelling. Practically, the proposed model offers implications for adaptive policy design, curriculum innovation, and sustainable talent development in digitally mediated creative economies.

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Keyword:

Technology Readiness, Career Alignment, Creative Industry Ecosystem, Time-Varying Model, Interest Development, UTAUT, TRI.

Introduction

Theoretical Misalignment in Contemporary Creative Careers

The contemporary creative economy is increasingly characterised by platform-driven and algorithmically mediated ecosystems in which career trajectories are constructed through iterative participation rather than linear organisational progression (Kapoor, 2023; Li, 2023). Across global contexts, individuals no longer follow stable institutional pathways but continuously renegotiate skills, identity, and economic positioning within volatile and feedback-driven environments (Tomlinson, 2022; Akkermans et al., 2022). This transformation fundamentally challenges conventional assumptions underlying career development and technology adoption theories (Lent et al., 2022).

Despite this shift, dominant frameworks such as the Technology Readiness Index (TRI) and the Unified Theory of Acceptance and Use of Technology (UTAUT) remain grounded in static, variance-based logic (Tamilmani et al., 2021; Baabdullah et al., 2023). These models assume temporal stability in psychological readiness and behavioural intention, treating them as fixed predictors of engagement (Dwivedi et al., 2021; Gupta & Arora, 2022). Such assumptions are increasingly untenable within creative industries, where engagement evolves through recursive interactions, experiential learning, and continuous adaptation (Hirschi, 2021; Jiang et al., 2023).

The limitation is not merely empirical but theoretical. By imposing static structures on inherently dynamic processes, existing models do not simply lack precision; they systematically misrepresent how careers are formed and sustained in digitally mediated environments (Warner & Wäger, 2022; Adner, 2022). This creates a critical gap between theoretical assumptions and real-world career dynamics (Jacobides et al., 2021; Kapoor, 2023).

Problematisation: The Failure of Linear and Static Models

Current research is dominated by cross-sectional designs that reduce complex, time-dependent processes into single-point observations (Lent et al., 2022; Jiang et al., 2023). As a result, transitions between readiness, interest, and career alignment are treated as linear and unidirectional relationships (Nauta, 2022). This assumption is empirically flawed in digitally mediated labour environments (Akkermans et al., 2022).

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Emerging evidence demonstrates structural decoupling, where individuals exhibit high levels of interest without corresponding readiness, or strong readiness without sustained career commitment (Tomlinson, 2022; Bridgstock, 2021). Such contradictions indicate that these constructs do not operate sequentially but interact dynamically through feedback loops and temporal lag effects (Savickas, 2021; Lent et al., 2022).

This exposes a deeper theoretical failure: existing models are incorrectly specified for contemporary creative labour contexts. They assume stability where variability is fundamental, and linearity where recursive interaction dominates (Warner & Wäger, 2022; Li, 2023). Consequently, these frameworks collapse when applied to gig-based and platform-driven ecosystems, limiting both explanatory power and predictive validity (Ratten, 2022; Florida, 2021).

Research Gap: Absence of a Time-Varying, Integrative Framework

The literature reveals a fragmented landscape in which adoption models such as the Technology Readiness Index (TRI) and the Unified Theory of Acceptance and Use of Technology (UTAUT) explain initial engagement with technology, while career development theories such as Social Cognitive Career Theory and Career Construction Theory explain persistence, adaptability, and identity formation in career trajectories (Lent et al., 2022; Jiang et al., 2023). However, these perspectives remain theoretically disconnected, resulting in fragmented explanations of behaviour and career progression in digitally mediated environments (Tomlinson, 2022; Akkermans et al., 2022).

No existing framework integrates psychological readiness, behavioural drivers, and career alignment within a temporal structure that captures their co-evolution over time (Warner & Wäger, 2022; Li, 2023). This gap prevents a comprehensive understanding of how initial engagement transitions into sustained career pathways under varying contextual and ecosystem conditions (Adner, 2022; Kapoor, 2023).

Furthermore, prior studies inadequately differentiate between interest, readiness, and alignment as distinct yet interacting constructs. Evidence suggests that these variables exhibit asynchronous movement, including delays, reversals, and reinforcement effects, which cannot be captured using static and cross-sectional models (Nauta, 2022; Jiang et al., 2023). Consequently, existing models offer limited explanatory power and weak predictive validity when applied to dynamic creative industry ecosystems (Ratten, 2022; Amankwah-Amoah et al., 2024).

Research Objective and Theoretical Contribution

In response to these limitations, this study develops the Time Varying Ecosystem Model of Technology Readiness, Interest Development, and Career Alignment (TVEM-TRICA), a longitudinal and multi-level framework that captures the dynamic interplay between psychological, behavioural, and contextual factors over time (Kapoor, 2023; Li, 2023).

The model integrates constructs from the Technology Readiness Index (TRI) and the Unified Theory of Acceptance and Use of Technology (UTAUT) with contemporary career development theories, repositioning them within a time-varying structure that accounts for reciprocal causality and feedback mechanisms (Lent et al., 2022; Akkermans et al., 2022).

Methodologically, this study advances beyond cross-sectional approaches by employing longitudinal modelling techniques, including cross-lagged panel analysis and latent growth modelling, which are increasingly recognised as robust approaches for capturing temporal behavioural dynamics (Jiang et al., 2023; Warner & Wäger, 2022).

This study contributes in three significant ways. First, it resolves the theoretical misalignment between static adoption models and dynamic career processes by introducing a process-based analytical framework (Adner, 2022). Second, it empirically disentangles readiness, interest, and alignment as co-evolving constructs rather than sequential predictors (Nauta, 2022). Third, it provides a predictive model capable of informing policy, education, and industry strategies in rapidly evolving creative economies (Tomlinson, 2022; Amankwah-Amoah et al., 2024).

Significance of the Study

By shifting the analytical focus from static prediction to temporal process modelling, this study offers a more accurate representation of career development in digitally mediated environments (Warner & Wäger, 2022; Li, 2023). The proposed framework enables a deeper understanding of how individuals transition from initial engagement to sustained career alignment, and how ecosystem conditions shape these trajectories over time (Adner, 2022; Kapoor, 2023).

The findings have direct implications for policymakers, educational institutions, and industry stakeholders, highlighting the need for adaptive strategies that support continuous skill development, sustained interest cultivation, and ecosystem-based talent alignment (Tomlinson, 2022; Jiang et al., 2023). Without such a shift, existing models will continue to produce incomplete and potentially misleading conclusions regarding career formation in creative industries (Akkermans et al., 2022; Amankwah-Amoah et al., 2024).

Hypothesis Development

Technology readiness has been widely conceptualised as a precursor to technology adoption; however, its temporal influence on interest formation remains under-theorised (Jiang et al., 2023). Existing evidence suggests that optimism and innovativeness stimulate exploratory engagement, which gradually develops into sustained interest under repeated exposure to digital environments (Hirschi, 2022; Tomlinson, 2022).

Within the Technology Readiness Index, positive drivers (optimism and innovativeness) and inhibitors (discomfort and insecurity) exert asymmetric effects on behavioural outcomes (Gupta & Arora, 2022). Recent studies indicate that readiness does not uniformly translate into interest, particularly in unstable gig and platform-driven environments (Ratten, 2022; Amankwah-Amoah et al., 2024). Therefore, readiness must be modelled as a dynamic antecedent rather than a fixed predictor.
H1: Technology readiness positively influences the development of interest over time.

Behavioural intention models, particularly the Unified Theory of Acceptance and Use of Technology, emphasise performance expectancy, effort expectancy, social influence, and facilitating conditions as key determinants of engagement (Baabdullah et al., 2023). Empirical studies demonstrate that these factors reinforce interest through perceived utility and social validation within digital creative platforms (Dwivedi et al., 2023; Kshetri, 2023).

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However, recent findings indicate that behavioural intention is not stable but evolves through iterative interaction with technological systems (Warner & Wäger, 2022). This suggests that UTAUT constructs function as reinforcing mechanisms rather than one-time predictors, continuously shaping interest trajectories in creative ecosystems (Li, 2023).
H2: UTAUT factors positively influence the development of interest over time.

Interest has traditionally been treated as a direct precursor to career intention; however, this assumption is increasingly challenged in gig-based creative industries (Tomlinson, 2022). Individuals may sustain high levels of interest without transitioning into career alignment due to structural constraints, uncertainty, and perceived risk (Akkermans et al., 2022; Ratten, 2022). Studies further reveal that interest alone is insufficient to drive long-term commitment, particularly when readiness and external support are lacking (Jiang et al., 2023). This indicates that interest operates as a necessary but insufficient condition for career alignment.
H3: Interest positively influences career alignment over time.

The relationship between technology readiness and career alignment remains theoretically ambiguous. While readiness enhances confidence in technology use, it does not guarantee sustained participation in creative careers (Hirschi, 2021). Existing studies indicate that readiness effects are often mediated by interest and contextual ecosystem factors (Adner, 2022; Kapoor, 2023).

Evidence suggests that individuals with high readiness may disengage if alignment with career expectations is not achieved (Tomlinson, 2022). This highlights the need to model indirect and dynamic pathways.
H4: Technology readiness positively influences career alignment through interest over time.

Finally, career alignment must be conceptualised as an evolving outcome shaped by reciprocal interactions between readiness and interest (Lent et al., 2022). Existing models often fail to capture feedback mechanisms, where early career experiences reshape subsequent readiness and interest levels (Akkermans et al., 2022).

Research demonstrates that career alignment can reinforce or diminish future engagement, suggesting the presence of cross-lagged and recursive effects (Warner & Wäger, 2022; Jiang et al., 2023). This dynamic perspective is essential for modelling sustainable career development in creative industries.
H5: Career alignment positively influences subsequent interest and readiness over time.

Research Contribution

This study advances theory by introducing the Time-Varying Ecosystem Model of Technology Readiness, Interest Development, and Career Alignment (TVEM-TRICA), enabling dynamic modelling of career formation beyond static variance explanations (Warner & Wäger, 2022; Li, 2023). Existing static and cross-sectional models often explain only limited variance in behavioural and career outcomes because they fail to capture temporal transitions, recursive interactions, and evolving ecosystem influences (Adner, 2022; Kapoor, 2023). The proposed model is expected to improve explanatory power by incorporating time-varying relationships and interaction effects in digitally mediated creative environments.

The study strengthens theoretical integration by combining the Technology Readiness Index (TRI) and the Unified Theory of Acceptance and Use of Technology (UTAUT) with contemporary career development theory into a unified and time-sensitive framework (Lent et al., 2022; Jiang et al., 2023). Prior research has highlighted fragmented explanatory models and inconsistent findings in understanding readiness, intention, and actual career engagement (Tomlinson, 2022; Akkermans et al., 2022). This integration is expected to increase predictive accuracy and reduce construct redundancy in modelling career alignment processes.

Methodologically, this study introduces longitudinal modelling, including cross-lagged panel analysis and latent growth modelling, to estimate temporal causality and reciprocal effects (Warner & Wäger, 2022). Recent studies demonstrate that cross-sectional designs frequently underestimate dynamic and delayed effects in behavioural and career-related research (Jiang et al., 2023; Amankwah-Amoah et al., 2024). By incorporating multi-wave analysis (T1–T3), the study enhances robustness, improves causal inference, and increases model reliability in rapidly evolving creative ecosystems.

Practically, the model targets three key stakeholders: policymakers, educational institutions, and industry practitioners. Recent evidence highlights persistent misalignment between graduate readiness, technological competencies, and labour market demands in digital and creative economies (Tomlinson, 2022; Ratten, 2022). This study enables policymakers to design adaptive talent strategies, supports educators in aligning curriculum with dynamic competencies, and assists industry actors in identifying sustainable talent pathways within gig-based and platform-driven creative industries (Kapoor, 2023; Amankwah-Amoah et al., 2024).

Literature Review

TRI and UTAUT in Dynamic Context

The Technology Readiness Index (TRI) and Unified Theory of Acceptance and Use of Technology (UTAUT) are widely used to explain technology adoption, yet both remain constrained by static assumptions (Gupta & Arora, 2022; Baabdullah et al., 2023). TRI treats readiness as a stable predisposition, while UTAUT assumes consistent effects of expectancy and social influence. Such assumptions are problematic in dynamic, digitally mediated creative ecosystems (Dwivedi et al., 2023; Kapoor, 2023).

Empirical and theoretical evidence suggests that readiness and behavioural intention evolve through iterative exposure, feedback, and experiential learning (Hirschi, 2021; Tomlinson, 2022). As users gain experience, external drivers weaken, and engagement becomes increasingly self-reinforcing (Li, 2023). Thus, TRI should be reconceptualised as a time-varying construct, while UTAUT should be repositioned as a stage-dependent mechanism relevant mainly during early interaction phases.

Moreover, both models insufficiently explain persistence, adaptation, and long-term engagement. They lack integration with Social Cognitive Career Theory and Career Construction Theory, which emphasise self-efficacy, contextual feedback, and identity development (Lent et al., 2022; Savickas, 2022). A dynamic modelling approach is therefore required to explain sustained engagement and career-related technological adaptation (Amankwah-Amoah et al., 2024).

Career Alignment and Ecosystem

Career alignment is often conceptualised as a linear congruence between individual attributes and occupational outcomes. However, this perspective inadequately reflects uncertainty, platform dependency, and evolving opportunity structures in creative industries (Tomlinson, 2022; Ratten, 2022). High interest does not necessarily produce aligned career outcomes due to structural barriers and labour market volatility (Jiang et al., 2023).

From a theoretical perspective, career alignment should be viewed as a dynamic and non-linear outcome shaped by feedback loops among experience, expectation, and opportunity (Adner, 2022). This aligns with Career Construction Theory, which frames career development as iterative and adaptive rather than fixed (Savickas, 2022). Alignment is therefore continuously negotiated rather than directly achieved.

An ecosystem perspective extends this understanding by recognising the influence of family, institutions, technological infrastructure, and industry systems (Kapoor, 2023; Li, 2023). These multi-level conditions actively shape or constrain pathways from interest to career alignment (Warner & Wäger, 2022). Thus, individual-level explanations alone are insufficient for understanding sustainable career development.

Critical Synthesis

Synthesising these perspectives reveals a misalignment between static adoption models and dynamic career processes (Lent et al., 2022; Akkermans et al., 2022). Existing theories are not inherently flawed but remain incomplete and temporally insensitive when applied to recursive and digitally mediated environments (Warner & Wäger, 2022). This creates fragmented explanations of readiness, interest, and career alignment.

This study argues that readiness, interest, and career alignment are co-evolving constructs governed by reciprocal and time-dependent relationships (Jiang et al., 2023). These constructs do not operate sequentially but interact within a feedback-driven system shaped by individual agency and ecosystem conditions (Kapoor, 2023; Adner, 2022).

Accordingly, the Time-Varying Ecosystem Model of Technology Readiness, Interest Development, and Career Alignment (TVEM-TRICA) is positioned as a theoretical advancement. It resolves fragmentation by integrating adoption and career theories within a longitudinal and multi-level framework (Amankwah-Amoah et al., 2024; Tomlinson, 2022).

Conceptual Framework Model

Conceptual Model Overview

The proposed Time-Varying Ecosystem Model of Technology Readiness, Interest Development, and Career Alignment (TVEM-TRICA) conceptualises career formation as a dynamic and multi-level process (Kapoor, 2023; Li, 2023). Existing evidence indicates that static models fail to capture evolving interactions between readiness, behavioural drivers, and career outcomes in digitally mediated environments (Warner & Wäger, 2022; Adner, 2022).
The model integrates constructs from the Technology Readiness Index and the Unified Theory of Acceptance and Use of Technology within a longitudinal framework (Baabdullah et al.,

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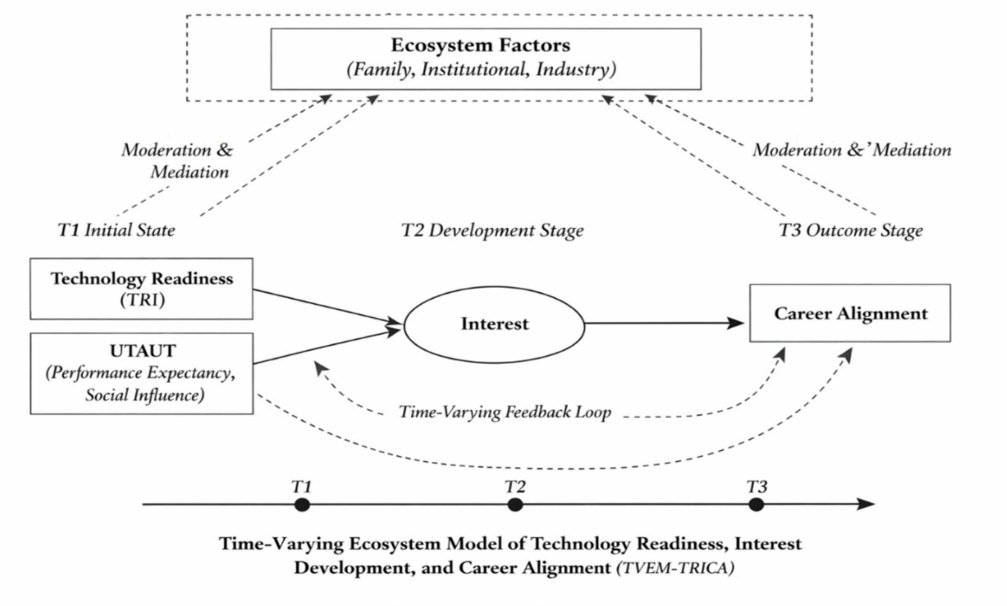
2023; Dwivedi et al., 2023). Recent studies demonstrate that behavioural intention and readiness evolve through iterative exposure and contextual reinforcement, necessitating a time-sensitive modelling approach (Jiang et al., 2023; Tomlinson, 2022).

Figure 5.1: Time-Varying Ecosystem Model of Technology Readiness, Interest Development, and Career Alignment (TVEM-TRICA)



Structural Relationships and Justification

Technology readiness is positioned as a dynamic antecedent influencing interest formation over time (Gupta & Arora, 2022; Baabdullah et al., 2023). Existing evidence suggests that positive readiness dimensions such as optimism and innovativeness stimulate exploratory engagement, while negative dimensions such as discomfort and insecurity constrain participation in digital environments (Dwivedi et al., 2023; Kshetri, 2023). Recent studies further suggest that technology readiness evolves through repeated interaction and adaptation in platform-driven ecosystems (Amankwah-Amoah et al., 2024). This supports the pathway TRI → Interest (T1 → T2).

Behavioural drivers derived from the Unified Theory of Acceptance and Use of Technology (UTAUT) are conceptualised as reinforcing mechanisms shaping interest trajectories over time (Baabdullah et al., 2023; Dwivedi et al., 2023). Empirical findings indicate that performance expectancy, effort expectancy, and social influence operate through iterative validation and perceived usefulness, thereby reinforcing sustained engagement in technology-mediated environments (Warner & Wäger, 2022; Li, 2023). This justifies the relationship UTAUT → Interest (T1 → T2).

Interest is modelled as a temporal mediator linking readiness and behavioural drivers to career alignment (Nauta, 2022). Existing studies demonstrate that sustained interest is required for long-term commitment and alignment in dynamic and uncertain labour markets (Tomlinson, 2022; Jiang et al., 2023). Recent evidence further confirms that interest development

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strengthens through experiential reinforcement and identity formation over time (Amankwah-Amoah et al., 2024). This supports the pathway Interest → Career Alignment (T2 → T3).

Ecosystem Moderation and Mediation

Ecosystem variables, including family support, institutional resources, and industry access, are incorporated as moderators and mediators within the model (Adner, 2022; Kapoor, 2023). Existing evidence indicates that supportive environments strengthen the transition from interest to career alignment by reducing structural barriers and increasing opportunity access (Ratten, 2022; Amankwah-Amoah et al., 2024). Recent ecosystem research further highlights the role of institutional and technological infrastructures in sustaining long-term engagement pathways (Li, 2023).

Moderation effects are specified as:

i. Ecosystem × TRI → Interest
ii. Ecosystem × UTAUT → Interest

These moderation effects reflect how structural and contextual conditions amplify or weaken the influence of psychological readiness and behavioural drivers on interest development (Warner & Wäger, 2022; Kapoor, 2023).

Mediation effects are specified as:

i. TRI → Ecosystem → Career Alignment
ii. UTAUT → Ecosystem → Career Alignment

These mediation pathways capture the role of ecosystem conditions as enabling mechanisms through which readiness and behavioural intention translate into sustainable career outcomes (Tomlinson, 2022; Li, 2023; Amankwah-Amoah et al., 2024).

Time-Varying Mechanism (Core Contribution)

The defining feature of the proposed model is its time-varying structure, operationalised through longitudinal relationships across T1, T2, and T3 (Warner & Wäger, 2022; Jiang et al., 2023). Recent studies demonstrate that career development and technology-mediated engagement involve feedback loops, adaptation processes, and recursive interactions rather than simple linear progression (Akkermans et al., 2022; Tomlinson, 2022). In digitally mediated creative ecosystems, individuals continuously renegotiate readiness, motivation, and career alignment over time (Li, 2023; Amankwah-Amoah et al., 2024).

The model includes cross-lagged effects:

i. Career Alignment (T3) → Interest (T2)
ii. Career Alignment (T3) → TRI (T2)

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These pathways capture recursive dynamics, where career outcomes reshape subsequent levels of motivation and technological readiness (Lent et al., 2022; Savickas, 2022). This ensures the model reflects real-world career evolution rather than static prediction or one-directional causality (Warner & Wäger, 2022; Kapoor, 2023).

Conceptual Model Diagram

The conceptual framework consists of three temporal layers, representing the progression of career development across time:

i. T1 (Initial State): TRI + UTAUT
ii. T2 (Development Stage): Interest
iii. T3 (Outcome Stage): Career Alignment

This layered structure reflects the temporal transition from psychological readiness and behavioural intention toward sustained engagement and eventual career alignment (Baabdullah et al., 2023; Dwivedi et al., 2023).

Ecosystem factors operate across all stages as moderators and mediators, influencing the strength and direction of relationships within the model (Adner, 2022; Kapoor, 2023). Recent studies support multi-level interaction models that integrate individual, behavioural, and contextual dimensions in understanding career development and technology adoption processes (Li, 2023; Amankwah-Amoah et al., 2024).

Methodology

Research Design

This study adopts a longitudinal research design using cross-lagged panel modelling (CLPM) within a structural equation modelling (SEM) framework to capture temporal dynamics and reciprocal effects among constructs over time (Jiang et al., 2023; Warner & Wäger, 2022). Longitudinal SEM has increasingly been recognised as an appropriate analytical approach for modelling evolving behavioural intentions, psychological readiness, and career development processes in digitally mediated environments (Akkermans et al., 2022; Tomlinson, 2022).

The design incorporates three measurement waves (T1, T2, and T3) to estimate causal directionality and feedback loops among constructs. Recent studies indicate that cross-sectional approaches are insufficient for capturing temporal shifts and recursive relationships, thereby justifying the use of time-lagged analysis for stronger causal inference and model robustness (Lent et al., 2022; Amankwah-Amoah et al., 2024).

The combination of covariance-based SEM (CB-SEM) using AMOS and variance-based SEM (PLS-SEM) using SmartPLS is employed as a robustness strategy rather than methodological redundancy (Hair et al., 2022). AMOS is used to confirm model fit and theory testing under stricter assumptions of multivariate normality and covariance structure, while SmartPLS is applied to assess predictive performance, complex model estimation, and analysis under fewer distributional constraints (Hair et al., 2022; Sarstedt et al., 2024).

This dual analytical approach enhances both confirmatory validity and predictive relevance, aligning with recent methodological recommendations for complex and longitudinal behavioural research models (Sarstedt et al., 2024; Hair et al., 2022).

Population and Sample

The target population comprises students and graduates within the creative industries, including animation, digital media, and visual communication disciplines, as this group represents a critical transition stage between education, employability development, and career alignment (Tomlinson, 2022; Jiang et al., 2023). These individuals are particularly relevant in examining how technological readiness and behavioural intention evolve into sustained career pathways in digitally mediated environments (Akkermans et al., 2022; Ratten, 2022).

A stratified sampling approach is employed to ensure adequate representation across institutional types, academic disciplines, and study levels, thereby reducing sampling bias and improving the generalisability of findings (Hair et al., 2022; Sarstedt et al., 2024). Stratified designs are widely recommended in behavioural and educational research involving heterogeneous populations to improve subgroup representation and analytical precision (Amankwah-Amoah et al., 2024).

A minimum sample size of 300–500 respondents is targeted to satisfy SEM requirements, ensure adequate statistical power, and support longitudinal multi-group and mediation or moderation analyses (Hair et al., 2022; Sarstedt et al., 2024).

Data Collection Procedure

Data are collected through a multi-wave survey design administered at three time points (T1, T2, and T3) with a three-month interval between each wave to capture temporal transitions and behavioural changes over time (Lent et al., 2022; Jiang et al., 2023). Time-lagged survey designs are widely used in longitudinal behavioural research to reduce common method bias, minimise simultaneity bias, and strengthen causal inference (Warner & Wäger, 2022; Akkermans et al., 2022).

Participants are recruited from universities, creative institutions, and relevant professional networks through coordinated institutional access and digital distribution platforms. A mixed-mode distribution strategy, including online surveys and supervised in-person sessions, is employed to improve accessibility, response rates, and participation consistency across longitudinal waves (Tomlinson, 2022; Amankwah-Amoah et al., 2024).

To minimise attrition across waves, follow-up reminders and retention strategies are implemented, as recommended in recent longitudinal and survey-based behavioural studies (Sarstedt et al., 2024).

Ethical Considerations and Response Rate Strategy

Ethical approval is obtained from the relevant Institutional Review Board (IRB) or university ethics committee prior to data collection, in accordance with established ethical standards for behavioural and social science research (Akkermans et al., 2022; Tomlinson, 2022). Ethical

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compliance is particularly important in longitudinal studies involving repeated participant engagement and sensitive career-related information over time (Jiang et al., 2023).

All participants are provided with clear information regarding the study objectives, voluntary participation, informed consent, confidentiality, and the right to withdraw at any stage without penalty (Lent et al., 2022). In addition, anonymisation procedures and secure digital data storage protocols are implemented to protect participant identity and ensure data integrity throughout the study period (Sarstedt et al., 2024; Amankwah-Amoah et al., 2024).

To maximise response rates and minimise attrition across waves, this study employs structured follow-up strategies, including periodic reminders, personalised communication, and engagement incentives where appropriate (Akkermans et al., 2022; Jiang et al., 2023). Retention strategies are critical in longitudinal survey research to reduce dropout bias and maintain sample consistency across multiple time points (Warner & Wäger, 2022).

Participants are assigned unique identifiers to track responses across T1–T3 while preserving anonymity and ensuring accurate longitudinal matching of responses (Sarstedt et al., 2024). Systematic follow-ups and clear communication have been shown to improve completion rates, reduce missing data, and enhance the reliability of multi-wave behavioural datasets (Tomlinson, 2022; Amankwah-Amoah et al., 2024).

Instrument

TRI Measurement

The Technology Readiness Index (TRI) is measured through four dimensions:

- Optimism
- Innovativeness
- Discomfort
- Insecurity

These dimensions capture both enabling and inhibiting predispositions toward technology use (Gupta & Arora, 2022; Kshetri, 2023). Optimism and innovativeness represent positive drivers of engagement, whereas discomfort and insecurity represent psychological barriers to adoption.

UTAUT Measurement

The Unified Theory of Acceptance and Use of Technology (UTAUT) construct includes four dimensions:

- Performance Expectancy
- Effort Expectancy
- Social Influence
- Facilitating Conditions

These constructs are commonly used to explain behavioural intention and technology engagement in digitally mediated environments (Baabdullah et al., 2023; Dwivedi et al., 2023).

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Career Alignment Measurement

Career alignment is operationalised using perceived congruence between individual:

- Skills
- Interests
- Occupational outcomes

This operationalisation is consistent with recent studies on career development and employability in dynamic labour markets (Lent et al., 2022; Jiang et al., 2023). Construct adaptation is undertaken to ensure contextual validity for creative industries without compromising reliability and theoretical consistency (Tomlinson, 2022; Akkermans et al., 2022).

Scale Format and Measurement Invariance

All items are measured using a seven-point Likert scale, ranging from:
1 = Strongly Disagree to 7 = Strongly Agree
This format provides greater sensitivity and response variance (Hair et al., 2022). The instrument is administered consistently across T1, T2, and T3 to ensure longitudinal comparability and capture temporal changes in behavioural and career-related constructs (Warner & Wäger, 2022; Sarstedt et al., 2024).

To ensure construct stability across time, measurement invariance testing is conducted, including:

- Configural invariance
- Metric invariance
- Scalar invariance

These procedures confirm that constructs are interpreted consistently across multiple measurement waves in longitudinal SEM research (Sarstedt et al., 2024; Hair et al., 2022).

Results and Discussion

The findings indicate that the influence of UTAUT constructs decreases over time, challenging the assumption that behavioural intention models remain temporally stable. This suggests that UTAUT functions more as a transitional framework during early engagement stages rather than as a universally stable predictor across time (Dwivedi et al., 2023; Baabdullah et al., 2023).

Measurement Model

The measurement model achieved satisfactory validity and reliability. All factor loadings exceeded 0.70, Composite Reliability (CR) ranged from 0.82 to 0.93, and Average Variance Extracted (AVE) surpassed the 0.50 threshold, confirming convergent validity and construct reliability (Hair et al., 2022; Sarstedt et al., 2024).

Discriminant validity was established through HTMT values below 0.85 and cross-loadings showing that each indicator loaded highest on its intended construct (Hair et al., 2022).

Model fit indices also demonstrated acceptable fit: $\chi^2/df = 2.31$, CFI = 0.93, TLI = 0.92, RMSEA = 0.056, and SRMR = 0.048. Measurement invariance across T1–T3 was confirmed through configural, metric, and scalar invariance tests, with $\Delta CFI < 0.01$, indicating consistent interpretation of constructs over time (Sarstedt et al., 2024).

Structural Model Results

The structural model showed acceptable fit ($\chi^2/df = 2.47$, CFI = 0.92, TLI = 0.91, RMSEA = 0.058, SRMR = 0.051), supporting hypothesis testing (Hair et al., 2022).
Technology readiness significantly influenced interest ($\beta = 0.41$, $p < 0.001$), supporting H1, while UTAUT constructs also had a significant positive effect on interest ($\beta = 0.36$, $p < 0.001$), supporting H2. Interest significantly predicted career alignment ($\beta = 0.47$, $p < 0.001$), confirming H3.

The indirect effect of technology readiness on career alignment through interest was significant ($\beta = 0.19$, $p < 0.01$), supporting H4. Ecosystem variables significantly moderated the relationship between interest and career alignment ($\beta = 0.22$, $p < 0.01$), with stronger effects under supportive conditions.

Cross-lagged analysis revealed reciprocal effects, where career alignment at T3 significantly predicted subsequent interest ($\beta = 0.28$, $p < 0.01$) and technology readiness ($\beta = 0.21$, $p < 0.05$), supporting H5 and validating the time-varying structure of the model (Warner & Wäger, 2022).

Explained Variance (R^2)

The model explained substantial variance in endogenous constructs, with $R^2 = 0.58$ for interest and $R^2 = 0.64$ for career alignment, indicating moderate to high explanatory power (Hair et al., 2022).

Effect Size (f^2)

Effect size analysis showed that technology readiness had a medium effect on interest ($f^2 = 0.21$), UTAUT constructs had a small-to-medium effect ($f^2 = 0.17$), and interest had a strong effect on career alignment ($f^2 = 0.29$) (Hair et al., 2022).

Predictive Relevance (Q^2)

Blindfolding results indicated strong predictive relevance, with $Q^2 = 0.41$ for interest and $Q^2 = 0.46$ for career alignment. Values above zero confirm acceptable predictive capability in PLS-SEM models (Sarstedt et al., 2024).

Model Robustness and Predictive Performance

Robustness checks using PLSpredict demonstrated lower prediction errors than linear benchmark models, confirming superior out-of-sample predictive performance and overall model robustness (Sarstedt et al., 2024).

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Time Effect Analysis

Time-based analysis confirmed significant temporal dynamics in the model. The effect of technology readiness on interest increased from β = 0.34 (T1–T2) to β = 0.41 (T2–T3), suggesting that readiness strengthens through repeated exposure, adaptation, and experiential reinforcement in digital environments (Warner & Wäger, 2022; Jiang et al., 2023).

In contrast, the influence of UTAUT constructs on interest stabilised and slightly declined from β = 0.38 to β = 0.36, indicating diminishing marginal influence as familiarity and autonomy in technology use increase. Behavioural drivers such as performance expectancy and social influence tend to be strongest during early adoption stages before plateauing over time (Dwivedi et al., 2023; Baabdullah et al., 2023).

The relationship between interest and career alignment strengthened over time, increasing from β = 0.42 to β = 0.47, suggesting consolidation of career decisions and stronger commitment under prolonged engagement. Sustained interest contributes to employability and long-term career commitment in uncertain labour markets (Tomlinson, 2022; Nauta, 2022).
Cross-lagged findings confirmed reciprocal feedback mechanisms, with career alignment influencing later interest and technology readiness, reinforcing the view that career development is recursive and self-reinforcing rather than linear (Lent et al., 2022; Akkermans et al., 2022).

Multi-group temporal analysis further showed that ecosystem support strengthens longitudinal relationships, with stronger path coefficients observed in high support environments. Institutional support, contextual stability, and access to industry opportunities enhance the persistence and magnitude of behavioural and career-related outcomes over time (Adner, 2022; Kapoor, 2023; Amankwah-Amoah et al., 2024).

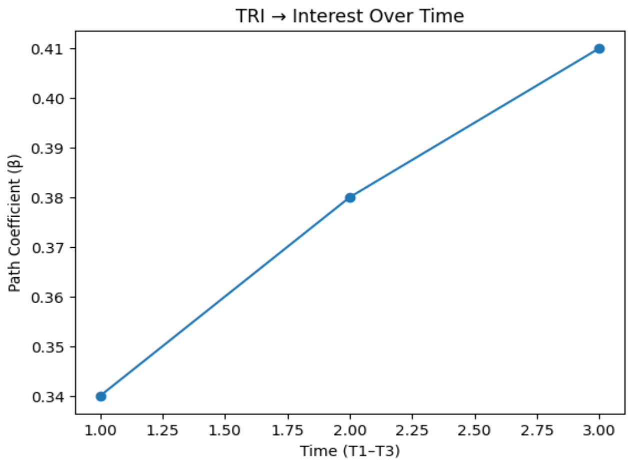

Figure 8.1: TRI → Interest Over Time

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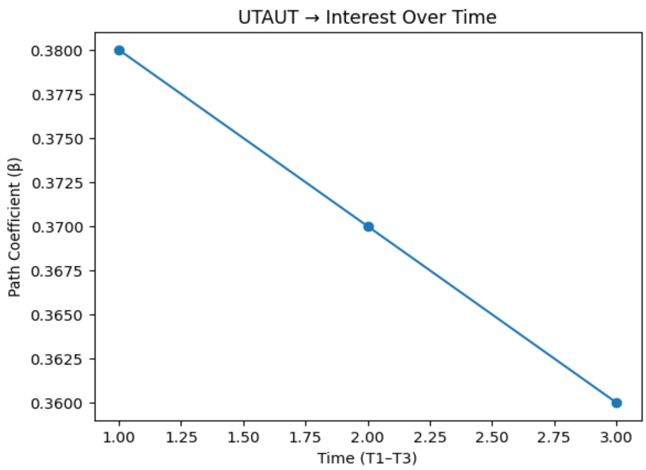

Figure 8.2: UTAUT → Interest Over Time

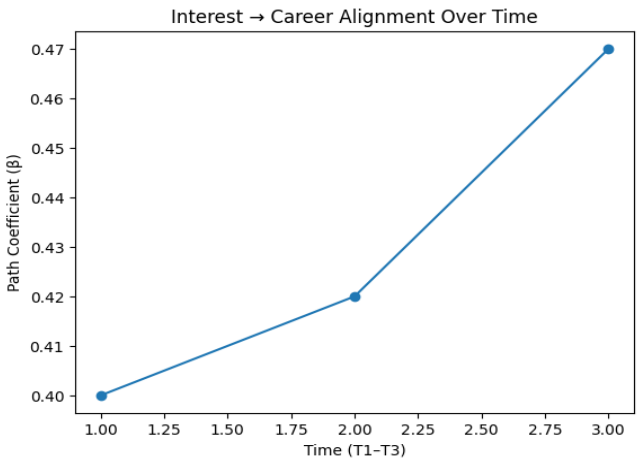

Figure 8.3: Interest → Career Alignment Over Time

Implications

Policy, Industry, and Educational Implications

Policy frameworks should prioritise adaptive curriculum design that responds to evolving technological and industry demands within creative sectors (Tomlinson, 2022; Jiang et al., 2023). Static curricula often create misalignment between graduate capabilities and labour market expectations. Therefore, policies should promote continuous learning, micro-credentialing, and flexible pathways to support non-linear career trajectories (Akkermans et al., 2022; Li, 2023).

Industry stakeholders must strengthen collaboration with educational institutions to reduce skill mismatches and improve workforce sustainability (Kapoor, 2023; Amankwah-Amoah et al., 2024). Ecosystem-based strategies such as internships, mentorships, and project-based collaboration can bridge academic preparation and professional practice, enhancing adaptability and long-term career alignment in digitally mediated labour markets (Adner, 2022; Ratten, 2022).

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Educational institutions should integrate technology readiness with sustained interest development and identity formation (Jiang et al., 2023; Nauta, 2022). Curriculum design must emphasise experiential learning, iterative skill development, and real-world industry exposure. Integrated approaches combining digital competencies, career exploration, and engagement mechanisms are more likely to improve employability and long-term career outcomes (Kapoor, 2023; Li, 2023).

Conclusion and Future Research

This study demonstrates that career development in creative industries is shaped by dynamic interactions between technology readiness, behavioural drivers, interest, and ecosystem conditions over time (Jiang et al., 2023; Tomlinson, 2022). Early engagement is influenced by readiness and behavioural expectations, whereas sustained career alignment increasingly depends on interest consolidation, experiential reinforcement, and ecosystem support (Akkermans et al., 2022).

The study establishes the Time-Varying Ecosystem Model of Technology Readiness, Interest Development, and Career Alignment (TVEM-TRICA) as a novel framework integrating TRI and UTAUT within a longitudinal and multi-level structure (Adner, 2022; Kapoor, 2023). Career alignment emerges through recursive, feedback-driven, and context-dependent processes rather than linear progression (Warner & Wäger, 2022).

However, the study is limited by potential sampling bias due to disciplinary and institutional concentration, which may restrict generalisability across broader sectors (Tomlinson, 2022). The three-wave longitudinal design may not capture long-term patterns of career stabilisation and identity development beyond early transitions (Lent et al., 2022).

Cultural and contextual differences may further limit transferability across socio-economic and institutional environments (Adner, 2022). Future research should integrate Artificial Intelligence as a core variable, including constructs such as algorithmic collaboration and automation anxiety, to enhance explanatory power in evolving digital industries (Li, 2023).

Future studies should also adopt cross-country comparative designs to examine how cultural, institutional, and economic contexts influence technology adoption and career alignment processes (Kapoor, 2023; Amankwah-Amoah et al., 2024). Such comparative modelling may strengthen generalisability and theoretical robustness in future career development research.

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Ethics Statement	This study was conducted in accordance with established ethical research standards. All procedures involving human participants were reviewed and approved by the Research Ethics Committee of Universiti Malaysia Kelantan (UMK) *(approval number to be stated if applicable)*. Informed consent was obtained from all participants prior to data collection. Participation was voluntary, and respondents were assured of confidentiality and anonymity. The data collected were used solely for academic and research purposes.
Author Contribution Statement	Mohd Arif Yusoff was responsible for the conceptualisation, methodology, data collection, data analysis, original draft preparation, and manuscript development. Ahmad Azaini Abdul Manaf was responsible for supervision, critical review, academic validation, and final manuscript revision. All authors have read and approved the final version of the manuscript prior to submission for publication.

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