# THE TIME-ORIENTED LEARNER: A FRAMEWORK FOR DESIGNING PERSONALIZED MOBILE INTERFACES TO ENHANCE TECHNOLOGY ACCEPTANCE AND SELF-EFFICACY, AND REDUCE COGNITIVE LOAD

**ZHAO XIN[1], SITI NAZLEEN ABDUL RABU[2]**

[1, 2]Centre for Instructional Technology and Multimedia, Universiti Sains Malaysia, Pulau Pinang, Malaysia
E-mail:  [1]zhaoxin@student.usm.my, [2]snazleen@usm.my*

**ABSTRACT**

Mobile learning (m-learning) design often relies on a one-size-fits-all, universal approach. This approach may create cognitive friction for some learners. This occurs when their inherent time orientation, a stable trait governing how individuals manage tasks and time, is misaligned with the interface's structure. This study introduces and evaluates Time-Oriented Personalized Interfaces (TOPI), a novel approach that aligns interface design with learners' monochronic, polychronic, or neutral dispositions. We investigated the effects of this temporal alignment on university students' technology acceptance, self-efficacy, and cognitive load. A sequential explanatory mixed-methods design was employed with 150 university students. In the quantitative phase, monochronic and polychronic learners were assigned to interact with either a personalized interface matched to their time orientation or a universal interface serving as a control. Neutral learners were assigned to the universal interface to assess its baseline effectiveness. Pre- and post-tests were used to measure the key variables. Subsequently, semi-structured interviews with 30 participants provided qualitative insights into their experiences. Quantitative results revealed that, for both monochronic and polychronic learners, using a temporally aligned interface led to significantly higher technology acceptance and self-efficacy, as well as significantly lower cognitive load, compared to the universal baseline. Qualitative analysis confirmed these findings, showing monochronic learners valued structured, sequential workflows while polychronic learners thrived in flexible, multitasking environments. The universal interface was found to be effective and cognitively manageable for neutral learners. This study makes a significant contribution by establishing time orientation as a critical, empirically validated dimension for personalization in m-learning. Theoretically, it extends Person-Environment Fit theory to the design of digital learning environments. Practically, it provides a novel framework (TOPI) with actionable principles that challenge the dominance of one-size-fits-all design by demonstrating a clear path toward creating more effective, adaptive, and user-centered learning systems. This study provides compelling evidence that while a generic interface may be adequate for neutral learners, it is suboptimal for those with stronger temporal dispositions. Designing adaptive interfaces that accommodate temporal diversity is a key strategy for enhancing learning quality beyond mere usability, offering a practical framework for creating more effective and engaging digital learning environments.

**Keywords:** *Time Orientation; Personalized Interface Design; Educational Technology; Mobile Learning; Cognitive Load; Person-Environment Fit; Adaptive Learning*.

## 1.  INTRODUCTION

In the ever-evolving landscape of digital education, mobile learning (m-learning) has emerged as a transformative instructional model, offering learners the flexibility to access educational content across temporal and spatial boundaries [1]. Unlike traditional classroom-based systems, m-learning is largely self-directed and event-driven, allowing users to integrate learning into diverse aspects of their daily lives [2]. However, this very flexibility presents new challenges in terms of learner engagement, particularly regarding how individuals manage their cognitive and behavioral interactions with m-interfaces. One underexplored but critical factor influencing these interactions is time orientation—a stable personality trait that governs how individuals perceive, structure, and allocate their time [3].

Time orientation is widely recognized as a critical individual-difference variable in understanding how users interact with temporally structured environments. It is typically categorized

into three distinct modalities: monochronic, polychronic, and neutral [4]. Specifically, monochronic individuals exhibit a strong preference for engaging in one task at a time, strict adherence to scheduled routines, and low tolerance for interruptions, reflecting a linear and sequential conception of time. In contrast, polychronic individuals tend to engage in multiple tasks simultaneously, exhibit greater temporal flexibility, and remain comfortable with frequent task-switching and interruptions, reflecting a dynamic and nonlinear temporal framework [5].

Adding nuance to this dichotomy, a neutral time orientation constitutes a distinct temporal profile—the middle ground between the other two modalities. It is characterized by a preference for moderate pacing and flexible engagement. Neutral-oriented learners typically avoid extremes; they are neither drawn to the high regularity of monochronic systems nor to the interactivity favored by polychronic users. They may become disoriented in overly structured or highly multitasking learning environments. Together, these distinctions underscore the critical role of time orientation in influencing interactions between learners and interfaces [6].

These time-oriented tendencies directly impact user-interface interaction in m-learning environments [7]. Numerous studies confirm that time orientation influences learners' expectations and behaviors regarding key UI design elements, such as navigation style, information density, feedback modality, and interactivity level. For example, polychronic learners are more engaged and satisfied with high-density layouts that support multitasking. Conversely, monochronic learners prefer low-density layouts and clearly defined task boundaries that enable focused, step-by-step learning [8]. Perceptual responses to system feedback also differ. Polychronic users report lower sensitivity to delays in interface loading time, suggesting that they tolerate asynchronous or nonlinear interactions more readily [9]. Similarly, navigation preferences differ. Monochrons prefer linear paths, while polychrons prefer circular or modular pathways [10].

This differentiation extends beyond user preferences to fundamental issues of user experience and system effectiveness. Time orientation is not merely a behavioral trait—it is a fundamental cognitive filter that affects how individuals perceive structure, pacing, and engagement in digital environments [11]. When interface design aligns with a learner's time orientation, they perceive the interface as easier to use, more useful, and more

satisfying. These perceptions are critical predictors of technology acceptance in m-learning and lead to higher self-efficacy [12]. For instance, monochronic learners tend to perform well in structured environments with clear timelines and sequential tasks, whereas polychronic learners do better with interactive, fluid navigation and concurrent tasks [6]. Conversely, when system designs disregard these time-based preferences, learners may experience cognitive dissonance, frustration, and ultimately, disengagement [13].

Despite the growing recognition of time orientation in psychology and organizational research, its application in user interface (UI) design, particularly in m-learning remains underdeveloped [14]. Most m-learning applications rely on universal interface models that prioritize accessibility and minimize complexity for the broadest possible user base [15]. These designs typically feature moderate interactivity, balanced visual density, and standardized task flows to reduce usability barriers. Preliminary findings from this study revealed that such universal interfaces may suit learners with neutral time orientations, whose engagement preferences lean toward adaptability without extremes. However, this functional fit does not extend to learners with stronger temporal dispositions. Monochronic and polychronic users often experience misalignment and friction when interacting with these universal models. Universal one-size-fits-all models overlook the temporal diversity that shapes learners' attention regulation, pacing, and task coordination. Consequently, interface-person mismatches compromise system usability and contribute to persistent disengagement and high attrition rates in m-learning contexts [16].

To address these gaps, this study proposes and evaluates Time-Oriented Personalized Interfaces (TOPI), a novel design approach that aligns interface structures with users' time-oriented tendencies. Drawing from interdisciplinary frameworks in time orientation theory, human-computer interaction, and person-environment fit theory, the study explores how tailoring UI features to monochronic, polychronic, and neutral learners can improve learning performance in m-learning contexts, such as technology acceptance, self-efficacy, and cognitive load. The following questions guide the research:

i. What are the differences in the effects of a Polychronic Interface designed for polychronic learners on learners' technology acceptance, self-efficacy, and cognitive load compared to the Neutral Interface?

ii. What are the differences in the effects of a Monochronic Interface designed for monochronic learners on learners' technology acceptance, self-efficacy, and cognitive load compared to the Neutral Interface?

iii. Does a Monochronic Interface designed for monochronic learners significantly reduce learners' cognitive load compared to the Neutral Interface?

iv. What are the reasons for learners' preferences for specific UI elements, and how can these insights be used to improve the design of future time-oriented personalized interfaces?

Building on these research questions, the study adopts a sequential explanatory mixed-methods design that integrates controlled experimentation with qualitative inquiry. This approach allows both quantitative validation of the proposed relationships and qualitative explanation of the underlying learner experiences. In the quantitative phase, a quasi-experimental design is employed to test hypotheses derived from the conceptual framework, examining how the alignment between learners' time orientation and interface design influences three interrelated constructs—technology acceptance, self-efficacy, and cognitive load—that collectively determine learning effectiveness in m-learning environments. Accordingly, the study proposed the following hypotheses:

For Research Question 1

$H_1$: Learners using the Polychronic Interface will report significantly higher levels of technology acceptance compared to those using the Neutral Interface.

$H_2$ : Learners using the Polychronic Interface will show a greater increase in self-efficacy compared to those using the Neutral Interface.

$H_3$ : Learners using the Polychronic Interface will report significantly lower levels of cognitive load compared to those using the Neutral Interface.

For Research Question 2

$H_4$ : Learners using the Monochronic Interface will report significantly higher levels of technology acceptance compared to those using the Neutral Interface.

$H_5$ : Learners using the Monochronic Interface will show a greater increase in self-efficacy compared to those using the Neutral Interface.

$H_6$ : Learners using the Monochronic Interface will report significantly lower levels of cognitive load compared to those using the Neutral Interface.

For Research Question 3

$H_7$ : Neutral learners using the Neutral Interface will report high levels of technology acceptance.

$H_8$ : Neutral learners using the Neutral Interface will demonstrate increased self-efficacy.

$H_9$ : Neutral learners using the Neutral Interface will report relatively low cognitive load.

By articulating these hypotheses, the present study advances the emerging discourse on personalized learning by positioning time-oriented interface design as a critical dimension of learner–system fit. In doing so, it aims to deepen theoretical understanding of temporal cognition within human–computer interaction while offering practical implications for the design of personalized m-learning systems.

## 2. RESEARCH METHODOLOGY

This study employed a sequential explanatory mixed-methods design grounded in the pragmatism paradigm [17]. This design integrates both deductive and inductive reasoning: the deductive phase (quantitative) tests the conceptual framework and validates hypotheses, while the inductive phase (qualitative) captures learners' subjective perceptions and reasoning behind interface preferences. Specifically, the quantitative component adopts a quasi-experimental, non-equivalent control group design to examine the effects of TOPI on learners' technology acceptance, self-efficacy, and cognitive load. To implement this design and test the effectiveness of time-oriented personalization against a generic baseline, participants were divided into five groups based on their time orientation, creating two parallel experimental conditions and one observational cohort. For polychronic learners, a treatment group (P1) utilized the personalized Polychronic Interface, while a control group (P2) employed the Neutral Interface. Similarly, for monochronic learners, a treatment group (M1) used the personalized Monochronic Interface while a control group (M2) used the Neutral Interface. Additionally, a group of neutral learners (N) was assigned to the Neutral Interface to assess its baseline effectiveness for this specific population. Following the quantitative phase, the qualitative phase utilizes semi-structured interviews further to explore the reasons behind learners' time-oriented preferences, providing interpretive depth to the statistical findings. This integration ensures methodological triangulation,

thereby enhancing the reliability and explanatory power of the research.

## 2.1 Participants and Context

The target population of this study comprised undergraduate students aged 17 to 22. This demographic is widely recognized for its high engagement with mobile technologies and frequent use of digital platforms for learning [18]. Previous research indicates that this age group tends to exhibit relatively stable temporal preferences, which makes them especially suitable for evaluating TOPI designs [19].

To ensure sample representativeness, a multi-stage sampling procedure was adopted, by combining convenience, cluster, and purposive sampling strategies. First, 200 second-year undergraduate students were recruited from a core course titled "Design Methods" at a comprehensive university in China. This course was selected due to its large enrollment, consistent academic content, and student homogeneity in prior exposure to digital design tools. These factors helped minimize confounding variables related to curriculum differences. Second, cluster sampling narrowed the sample size within this course, allowing for manageable yet diverse learner groups. Finally, purposive sampling was applied to ensure balanced representation across time orientations: 60 polychronic, 60 monochronic, and 30 neutral learners, identified using the scale of polychronic in IT-supported learning (SPITSL) scores [20]. The participants were divided into five subgroups (P1, P2, M1, M2, and N), each comprising 30 students.

## 2.2 Instrument

To measure the key variables in this study, four validated instruments were employed. Learners' time orientation was assessed using the SPITSL [20], which was selected because it was specifically developed for m-learning contexts. The scale comprises 13 items across three constructs—Time Tangibility, Scheduling Preference, and Involvement with People—rated on a 5-point Likert scale. Its demonstrated reliability ($\alpha$ = 0.84–0.89) and clear differentiation of monochronic, polychronic, and neutral tendencies ensured accurate classification of participants. To evaluate learners' confidence in handling digital tasks, the Computer Self-Efficacy Measure [21] was adopted. Its 11-point scale provides fine granularity, making it especially suitable for detecting subtle changes in self-efficacy across pre- and post-tests, with reliability consistently above 0.80 in prior studies.

Technology acceptance was measured using the Technology Acceptance Questionnaire [22], adapted from the Technology Acceptance Model and contextualized for m-learning. This 23-item instrument covers Perceived Usefulness, Perceived Ease of Use, Attitude, and Behavioral Intention, and has shown satisfactory internal consistency ($\alpha$ = 0.76–0.87), supporting its effectiveness for pre–post comparisons. Finally, learners' cognitive load was assessed using the NASA-TLX scale [23], a multidimensional tool that evaluates mental, physical, and temporal demands, effort, performance, and frustration on a 20-point scale. With strong validity and reliability ($\alpha$ > 0.80), the NASA-TLX provides a comprehensive assessment of intrinsic, extraneous, and germane cognitive load, making it well-suited to the complexity of mobile learning tasks.

## 2.3 Treatment Materials

The treatment materials for this study comprise a series of TOPI designed to align with learners' temporal tendency. The development of these personalized interfaces followed a structured, evidence-based process encompassing four key phases: (1) the selection of relevant UI elements; (2) the formulation of time-oriented UI design guidelines; (3) the integration of cognitive design theories and international standards; and (4) the prototyping of interface designs using professional tools. For a baseline comparison, the Neutral Interface was designed based on common m-learning application principles and the ISO 9241-400 framework, without any specific tailoring to a particular time orientation. This interface aimed to represent a high-quality, 'one-size-fits-all' model. While its design principles of moderate pacing and balanced density may align well with the neutral time orientation, it was developed primarily as a generic control condition against which to test the effects of time-oriented personalization.

## 2.2.1 Development of Time-Oriented Design Guidelines

Building upon an extensive literature review in time-orientation, human-computer interaction, and educational technology, the researcher identified behavioral differences and personal preferences among three temporal types: monochronic, polychronic, and neutral orientation. Then, the study mapped these differences to interface-related elements and identified nine key UI elements that demonstrated significant relevance to time orientation. These elements include icon, color, information density, function, navigation,

interactive model, task mode, layout, and waiting time. The preliminary design mappings were validated through a UI preference survey conducted during the pilot phase, ensuring construct alignment and user interpretability.

### 2.2.2 Integration Interface

To optimize cognitive and ergonomic congruence, the interface development process incorporated multiple validated frameworks. First, time-based interaction preferences were cross-referenced with ISO 9241-400, a globally recognized standard for universal interface design in human-computer interaction. This ensured that each interface adhered to evidence-based usability principles, particularly relevant to m-learning environments. Additionally, the design of all interfaces was informed by Cognitive Load Theory [24] and Mayer's Multimedia Learning Principles [25]. These principles emphasize reducing extraneous load, facilitating intrinsic processing, and enhancing germane cognitive activity. Through integrating these interdisciplinary frameworks, the study derived three structured sets of interface design guidelines, each aligned with a specific time orientation. Notably, while the Neutral Interface was grounded in the ISO 9241-400 framework to ensure broad usability, it was not implemented as a static or generic model. Drawing on findings from prior literature and pilot-phase UI preference surveys, targeted refinements were made to elements such as visual density, navigation, and function. These adjustments were intended to align with the moderate pacing and situational adaptability of neutral time-oriented learners. Table 1 presents interface design guidelines for different time orientations.

*Table 1: Different Time-Oriented Interface Design Guidelines.*

| Element | Monochronic Interface | Polychronic Interface | Universal Interface |
|---|---|---|---|
| Icon | Font icons | Graphical icons | Icons combine graphics and text. |
| Color | Low-contrast colors | High-contrast colors | Balanced-contrast color |
| Density | Medium density | High-density | Balanced density |
| Function | Prefers scheduling tools and time management features | Prefers interactive discussion tools, flexible workspaces | Includes base functions for all learners |
| Layout | Infinite list layout | Thumbnail list layout | Structured list layout |

| Interactive Model | Limits real-time feedback | Timely feedback via animations, | Standardized interactive elements |
|---|---|---|---|
| Task Mode | Focuses on one task at a time | Uses split-screen layouts for simultaneous tasks | Focus on one task at a time (provide options for less important tasks) |
| Navigation | Linear, step-by-step navigation | Circular, flexible navigation | Structured menu-based navigation |
| Waiting time | Use a progress bar to indicate the waiting time progress clearly | Uses animated loading screens to reduce perceived waiting time | Uses standardized waiting visuals |

Subsequently, three interface prototypes were developed in accordance with the derived design specifications. The prototyping process employed Figma, a professional-grade, component-based UI design platform chosen for its interactive prototyping capabilities, modular system architecture. Through Figma's dynamic component libraries, each interface achieved high levels of usability, cognitive alignment, and visual consistency, ensuring technical robustness and pedagogical relevance. The figure 1, 2, and 3 show monochronic, polychronic, and neutral interface designs. For a more comprehensive overview of the interface design elements and layout, refer to Appendix 2, 3, and 4.
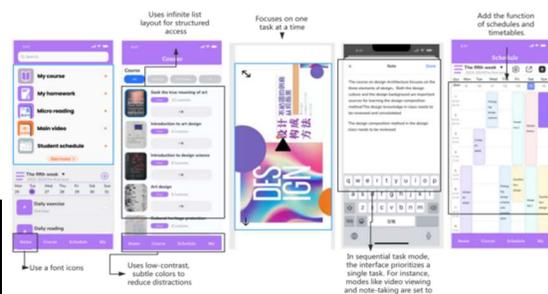


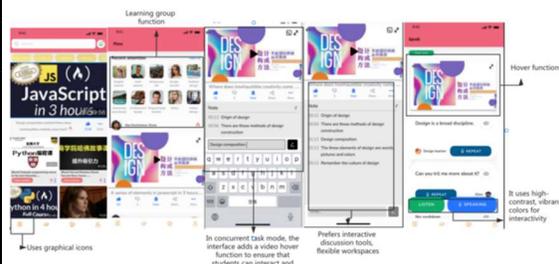*Figure 1: The Interface Design for Monochronic Learners*



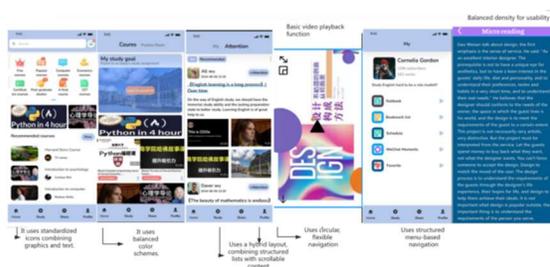*Figure 2: The Interface Design for Polychronic Learners*

*Figure 3: The Interface Design for Neutral Learners*

Importantly, to ensure experimental control, all interfaces delivered identical instructional content: a 30-minute video and accompanying study materials. These materials were carefully selected for their universal accessibility and conceptual neutrality. They avoided technical language or disciplinary complexity that could confuse learners. This ensured that any observed differences in learning outcomes could be reliably attributed to interface design rather than content variation.

## 2.4 Procedure and Data Collection

The experimental procedures were implemented in controlled laboratory-classroom settings to ensure environmental consistency and to minimize external interference or uncontrolled variability. Consistent with the overarching sequential explanatory mixed-methods design, the study was conducted in two phases: an initial quantitative phase followed by a qualitative phase.

In the pre-intervention stage, all 150 participants completed two pretests: the Technology Acceptance and Self-Efficacy scales, which measured their initial attitudes and confidence toward m-learning technologies. To mitigate potential novelty effects associated with unfamiliar digital environments, each participant was provided with a 10-minute guided familiarization session. During the treatment phase, participants engaged in a 60-minute self-directed m-learning task using the assigned interface based on their time orientation group. Specifically, monochronic learners in the M1 group used the Monochronic Interface, monochronic learners in the M2 group used the Neutral Interface, polychronic learners in the P1 group used the Polychronic Interface, polychronic learners in the P2 group used the Neutral Interface, and neutral learners in the N group used the Neutral Interface. Each group was assigned to a separate classroom within the university's laboratory environment to prevent cross-group interaction or contamination.

Following the treatment phase, post-tests were administered using the Technology Acceptance Questionnaire [21], the Computer Self-Efficacy

Scale [22], and the NASA-TLX Cognitive Load Scale [23] to assess learners' technology acceptance, self-efficacy, and mental workload. All instruments used in the post-test phase were identical to their pretest counterparts, allowing for robust pre–post comparisons. In the qualitative phase, semi-structured interviews were conducted with a purposive subsample of 30 participants (10 from each time orientation group). These interviews aimed to explore learners' subjective experiences, perceived usability, and design preferences related to the time-oriented interfaces.

## 2.5 Data Analysis

The data analysis followed a sequential approach corresponding to the study's mixed-methods design. Quantitative analyses were conducted using Social Sciences (SPSS) software, while qualitative data were analyzed in NVivo to provide interpretive depth.

To evaluate the effects of TOPI on learners' technology acceptance, self-efficacy, and cognitive load (RQs 1–3), a series of descriptive and inferential statistical tests was performed. First, descriptive statistics were computed to examine baseline equivalence across the five experimental conditions (M1, M2, P1, P2, and N) and verify assumptions of normality, homogeneity of variance, and data completeness. These checks ensured that the data met the assumptions required for parametric testing. To test the nine directional hypotheses ($H_1$–$H_9$), independent samples t-tests were employed to compare outcome variables between matched and unmatched interface–user conditions. Specifically, polychronic learners using the Polychronic Interface (P1) were compared to those using the Neutral Interface (P2), and monochronic learners using the Monochronic Interface (M1) were compared to their counterparts using the Neutral Interface (M2). For neutral learners (N), pre–post gains were assessed using paired samples t-tests, as they interacted with the Neutral Interface. All statistical tests were conducted at a significance level of 0.05. Additionally, effect sizes (Cohen's d) were computed to assess the magnitude of the differences and improve the interpretability of the results. This analytical framework ensured both statistical rigor and practical relevance in evaluating whether interface–learner temporal alignment produced measurable learning benefits.

To further explore Research Question 4, 30 participants were randomly selected from the monochronic, polychronic, and neutral groups for semi-structured interviews. A hybrid inductive-deductive thematic analysis was adopted [25].

Thematic coding focused on key constructs, including temporal alignment, UI element preferences, perceived usability, self-efficacy dynamics, and cognitive effort. To enable structured comparison across learner groups, matrix coding queries and node frequency analyses were performed. This analytical process provided a rich interpretive complement to the quantitative results, offering deeper explanations of how interface-time orientation congruence influenced learner perception, engagement, and cognitive processing.

## 3. RESULTS

### 3.1 Participant Demographics

The final sample consisted of 150 participants, comprising 76 males and 74 females, aged between 17 and 22 years (M = 19.6, SD = 1.2), which met the criteria for a statistically sufficient and demographically homogeneous sample for experimental control. Table 2 shows their demographics.

*Table 2: Demographic Profile.*

| Characteristic | Category | Frequency (f) | Percentage (%) |
|---|---|---|---|
| Gender | Female | 76 | 45.0 |
| | Male | 74 | 55.0 |
| Age | 17-19 | 104 | 69.3 |
| | 20-22 | 46 | 30.7 |

### 3.2 Effects of the Polychronic Interface on Learners' Technology Acceptance, Self-Efficacy, and Cognitive Load (RQ1)

This section presents findings related to RQ1, which examines the impact of a polychronic interface—specifically designed for polychronic learners—on technology acceptance, self-efficacy, and cognitive load, compared to a neutral interface. After validating normality and variance assumptions, independent samples t-tests were conducted, and all variables met the criteria for parametric testing. Table 3 summarizes the mean (M) and standard deviation (SD) of polychronic learners' scores across two interface conditions for the three key outcome variables.

*Table 3: Descriptive statistics for technology acceptance, self-efficacy, and cognitive load among polychronic learners in different groups.*

| Construct | Group | M | SD |
|---|---|---|---|
| Technology Acceptance | P-1 | 1.9 | 0.43 |
| | P-2 | 0.34 | 0.42 |
| Self-Efficacy | P-1 | 4.31 | 0.55 |
| | P-2 | 1.04 | 0.79 |
| Cognitive Load | P-1 | 9.33 | 1.29 |
| | P-2 | 12.46 | 1.92 |

An independent samples t-test revealed that learners using the Polychronic Interface reported significantly higher technology acceptance gain scores (M = 1.90, SD = 0.43) than those using the Neutral Interface (M = 0.34, SD = 0.42), t(58) = 14.11, p < .001, MD = 1.56, 95% CI [1.34, 1.78], Cohen's d = 3.64. Levene's test for equality of variances was non-significant (p = .97), confirming the assumption of equal variances. The extremely large effect size indicates that temporal alignment in interface design substantially enhances learners' perceived ease of use and engagement with the system, providing strong empirical support for H$_1$.

This pattern of improvement extended to self-efficacy. Learners in the Polychronic Interface group (M = 4.31, SD = 0.55) reported significantly higher self-efficacy gain scores than those in the Neutral Interface group (M = 1.04, SD = 0.79), t(58) = 18.62, p < .001, MD = 3.27, 95% CI [2.91, 3.62], Cohen's d = 4.79. Levene's test indicated equal variances (p = .07). The extremely large effect size suggests that temporal alignment in interface design markedly improves learners' confidence and their perceived ability to navigate and utilize the system effectively, providing strong empirical support for H$_2$.

Additionally, learners using the Polychronic Interface experienced a significantly lower cognitive load (M = 9.33, SD = 1.29) than those using the Neutral Interface (M = 12.46, SD = 1.92), t(50.93) = –7.39, p < .001, MD = –3.13, 95% CI [–3.98, –2.28], Cohen's d = 1.90. Given the significant result of Levene's test (p = .007), Welch's t-test was applied. The very large effect size indicates that the Polychronic Interface effectively minimized learners' mental processing demands by providing an interaction structure aligned with their time preference, providing strong empirical support for H$_3$.

Overall, the results across the three dimensions demonstrate the effectiveness of a temporally aligned interface design for polychronic learners. The Polychronic Interface increased self-efficacy and acceptance while reducing cognitive effort. These results reinforce the importance of the TOPI model in m-learning.

### 3.3 Effects of the Monochronic Interface on Learners' Technology Acceptance, Self-Efficacy, and Cognitive Load (RQ2)

This section presents the results of statistical analyses for RQ2, which examines the effects of a Monochronic Interface, designed for monochronic learners, on technology acceptance, self-efficacy, and cognitive load compared to the Neutral Interface. Independent samples t-tests were conducted, and all normality and variance assumptions were met or appropriately adjusted for, ensuring the validity of the results. Table 4 shows the descriptive results for monochronic learners under different interface conditions.

*Table 4: Descriptive statistics for technology acceptance, self-efficacy, and cognitive load among monochronic learners in different groups.*

| Construct | Group | M | SD |
|---|---|---|---|
| Technology Acceptance | M-1 | 1.71 | 0.29 |
| | M-2 | 0.06 | 0.24 |
| Self-Efficacy | M-1 | 3.59 | 1.52 |
| | M-2 | 1.17 | 0.65 |
| Cognitive Load | M-1 | 9.27 | 1.56 |
| | M-2 | 12.22 | 1.67 |

An independent samples t-test revealed that learners using the Monochronic Interface reported significantly higher technology acceptance gain scores (M = 1.71, SD = 0.29) compared to those using the Neutral Interface (M = 0.06, SD = 0.24), $t(58) = 24.20$, $p < .001$, MD = 1.65, 95% CI [1.51, 1.79], Cohen's d = 6.26. Levene's test for equality of variances was non-significant (p = .29), confirming the assumption of homogeneity. The extremely large effect size indicates that temporal congruence in interface design substantially enhances monochronic learners' technology acceptance and willingness to engage with the system, providing strong empirical support for H4.

This positive effect also extended to self-efficacy. Learners in the Monochronic Interface group (M = 3.59, SD = 1.52) reported significantly higher self-efficacy gain scores than their counterparts using the Neutral Interface (M = 1.17, SD = 0.65), $t(39.11) = 7.80$, $p < .001$, MD = 2.42, 95% CI [1.81, 3.03], Cohen's d = 2.01. Given the significant result of Levene's test (p < .001), Welch's t-test was applied. The very large effect size suggests a notable improvement in learners' confidence attributable to the temporal alignment between interface design and monochronic learning preferences, providing strong empirical support for H5.

In addition to improving technology acceptance and self-efficacy, the Monochronic Interface provided significant cognitive benefits. Learners in the Monochronic Interface group reported a significantly lower cognitive load (M = 9.27, SD = 1.56) than those in the Neutral Interface group (M = 12.22, SD = 1.67), $t(58) = -7.06$, $p < .001$, MD = –2.94, 95% CI [–3.78, –2.11], Cohen's d = 1.82. Levene's test was non-significant (p = .78), supporting the assumption of equal variances. The very large effect size provides compelling statistical evidence that time-oriented personalization in interface design reduces learners' perceived mental effort, providing robust support for H6.

These results collectively confirm all three hypotheses with strong statistical significance. Compared to the Neutral Interface, the personalization interface significantly improved technology acceptance, enhanced self-efficacy, and reduced cognitive load among learners with a monochronic time orientation.

### 3.4 Effects of the Neutral Interface on Neutral Learners' Technology Acceptance, Self-Efficacy, and Cognitive Load (RQ3)

This section examines whether the Neutral Interface reduces cognitive load and enhances technology acceptance and self-efficacy. To make a meaningful comparison, one-sample t-tests were conducted using benchmark values derived from the average pre-post differences in the P-2 and M-2 groups. Table 5 presents the descriptive results for neutral learners.

*Table 5: Descriptive Statistics for Technology Acceptance, Self-Efficacy, and Cognitive Load among Neutral Learners.*

| Construct | Group | M | SD |
|---|---|---|---|
| Technology Acceptance | N | 0.15 | 0.27 |
| Self-Efficacy | N | 1.23 | 0.38 |
| Cognitive Load | N | 10.04 | 1.5 |

Learners in the N group reported an average technology acceptance gain score of M = 0.15 (SD = 0.27). A one-sample t-test comparing this value to the benchmark gain (M = 0.19) indicated no statistically significant difference, $t(29) = -1.08$, $p = .29$, with a small effect size (d = 0.20, 95% CI [–0.16, 0.05]). This result indicates that H7 was not statistically supported. However, a deeper analysis of baseline and result data provides important contextual insight. Specifically, learners in the N group had substantially higher pretest technology acceptance scores (M = 3.42) than their counterparts

in the P-2 (M = 3.08) and M-2 (M = 3.06) groups. Despite the lack of significant improvement, their post-test means score (M = 3.57) exceeded the final scores of the comparison groups. This pattern suggests a classic ceiling effect, wherein learners with high initial perceptions have limited room for statistically meaningful improvement. In such cases, the absence of change does not imply ineffectiveness. Rather, it reflects the system's ability to sustain favorable learner dispositions, particularly among those with a neutral time orientation and positive prior attitudes toward m-learning applications.

A similar pattern emerged for self-efficacy. The N group's self-efficacy gain score (M = 1.23, SD = 0.38) was slightly lower than the benchmark value (M = 1.37). The one-sample t-test revealed that this difference was not statistically significant, t(29) = –1.99, p = .06, with a small-to-moderate effect size (d = 0.36, 95% CI [–0.28, 0.00]). Again, closer inspection reveals that the group's elevated starting point better explains this limited change. With a pretest self-efficacy mean of M = 4.78, the N group learners entered the study with the highest perceived competence, compared to the P-2 group (M = 4.53) and the M-2 group (M = 5.03). While their post-test score rose to M = 6.08, the magnitude of this improvement was attenuated by a diminishing returns effect, common in educational contexts where baseline levels approach the upper bounds of a measurement scale. From this perspective, while H8 was not statistically supported, the data suggest that the Neutral Interface effectively maintained self-efficacy among neutral learners who were already highly motivated.

In contrast, cognitive load showed statistically significant results. Learners in the N group reported a mean cognitive load of M = 10.04 (SD = 1.50), which was significantly lower than the average benchmark (M = 12.34). The one-sample t-test revealed a significant difference, t(29) = –8.40, p < .001, with a large effect size (d = 1.53, 95% CI [–2.86, –1.74]). These findings support H9, indicating that the Neutral Interface was particularly effective in minimizing the perceived mental burden among neutral learners.

Taken together, these findings demonstrate that while the Neutral Interface may not yield significant gains in acceptance or self-efficacy for learners who already possess strong cognitive and motivational readiness, it plays a crucial role in sustaining high performance and reducing cognitive strain. This suggests that the strength of the Neutral Interface lies not in transformative change but in its stabilizing function—providing a balanced, cognitively manageable environment well-suited for general learning populations, especially those with neutral time-orientation preferences. Such stability is particularly valuable in diverse educational contexts where learner readiness and disposition vary widely.

## 3.5 Learners' Reasons for UI Element Preferences (RQ4)

To investigate learners' preferences for specific UI elements, a semi-structured interview was conducted with 30 participants, equally distributed across three-time orientations (see Appendix 1). Thematic analysis revealed five major themes: Temporal Alignment and UI Fit, Satisfaction with UI Elements, Technology Acceptance, Self-Efficacy, and Cognitive Load. These themes illuminate how time orientation influences learners' interpretation and experience of m-learning interfaces. Table 6 presents the themes along with their respective categories and illustrative quotes.

*Table 6: Summary Of Thematic Analysis.*

| Theme | Category | Illustrative Quotes |
|---|---|---|
| Temporal Alignment | Sequential vs. Modular Workflow | "Every task is lined up in a single, logical sequence." (M5); "I arrange blocks like tasks, videos, and notes as I wish." (P5) "Hybrid layout is not too rigid, but it still helps me keep track of progress." (N3) |
| | Multitasking Preferences | "I prefer flexible, concurrent learning." (P2); "Focusing on one task at a time keeps me calm." (M3) |
| | Personality and Control | "I would like to customize my dashboard." (M4); "I found the interface supports personalized configuration." (P8) |
| UI Element Preference | Layout, Icons, Feedback | "Hybrid layout balances overview and detail." (N4) "Text-only icons help me focus." (M1) "Graphical icons stand out when I multitask." (P9) |
| | Task Mode | "Jumping between tasks keeps me inspired." (P3); "Checklists help me feel secure." (M4); |
| Technology Acceptance | Engagement, Attitude Shift, Frustration | "I was more willing to explore and try things." (P2); "Neutral Interface was overwhelming." (M3) |

| Self-Efficacy | Task Confidence, Control, Frustration | "I felt confident finishing every task." (M4); "By week two, I felt I was 'controlling' the system." (P6) |
|---|---|---|
| Cognitive Load | Mental Demand, Temporal Demand, Frustration | "Too many pop-ups distract me." (M3); "Page refreshed — content gone. It was very frustrating." (P3) |

### 3.5.1 Temporal Alignment and UI Fit

The perceived alignment between interface structure and learners' time orientation proved to be a key determinant of usability and comfort. Monochronic learners consistently expressed a preference for structured sequences, fixed layouts, and predictable task flows. This group reported enhanced clarity and reduced anxiety when interfaces followed clearly defined, step-by-step routines—aligning with their cognitive emphasis on order and progression. One learner noted that such linearity "lined up tasks in a single, logical sequence" (M5), reinforcing a sense of procedural control.

Conversely, polychronic learners responded more favorably to nonlinear, modular workflows that allowed simultaneous access to tasks and flexible navigation (P2). They described the interface as a dynamic "block" rather than a fixed path (P5), emphasizing the need for concurrent access and fluid task organization. In contrast, neutral learners exhibited balanced preferences, favoring hybrid designs that allowed for moderate switching without compromising clarity (N3). Rather than aligning with either extreme, they preferred interfaces that allowed controlled variability and consistent visual orientation. Additionally, neutral learners displayed a balanced orientation, valuing hybrid layouts that allowed adaptive switching between structured sequences and open modules (N4). These differences validate the premise that temporal orientation functions as a core moderator of UI expectations. When the interface aligned with temporal logic, learners experienced ease and engagement. When misaligned, the system generated disorientation or disengagement.

### 3.5.2 Satisfaction with UI Elements

Analysis of semi-structured interview data revealed clear patterns in learners' preferences for UI elements. Each time orientation group exhibits distinct top three priorities. While certain design features—such as layout, task models, and visual clarity—were universally appreciated, their perceived utility and optimal configurations diverged significantly based on time orientation.

Monochronic learners prioritized a structured layout (10/10), detailed progress feedback (10/10), and simplicity of icons (8/10). These learners consistently emphasized "checklists," "step-by-step flow," and "text-only icons," reflecting a cognitive preference for order and task closure (M4). Additionally, low-contrast visuals and moderate information density were noted to lower perceived cognitive load, reinforcing their need for minimal visual distractions (M1).

Conversely, polychronic learners demonstrated a strong preference for interactive, modular layouts (10/10) and multitasking capabilities (9/10). Learners in this group highlighted the ability to "jump between tasks" or "open multiple modules at once" as enabling creative autonomy and maintaining engagement across tasks (P6). While visual clarity indicators were acknowledged, they remained less important than workflow adaptability and nonlinear access. (P9) As one participant noted, "Modular panels let me work on multiple things"—an indication that high interactivity is not merely tolerated, but actively sought in interface use.

Neutral learners favored hybrid layouts that blended structure with adaptability (8/10), alongside moderate pacing control and navigational flexibility (10/10). This reflects their ergonomic preference for systems that avoid both rigidity and overload. Their satisfaction was often linked to moderate visual complexity—such as hybrid iconography (7/10) and medium visual density (N5)—which facilitated efficiency without cognitive strain.

### 3.5.3 Technology Acceptance

Technology acceptance across learner groups was not merely a response to interface usability but hinged critically on the perceived alignment between interface behavior and temporal expectations. Polychronic learners exhibited curiosity-driven engagement and positive attitude shifts when interface functions enabled concurrent tasks and switching. Learners described the system as "flexible" and "explorable" (P2). However, they became frustrated when design constraints, such as limited interactivity in discussion modules, prevented them from multitasking creatively (P2). Monochronic learners showed conditional

acceptance. Their engagement increased when the interfaces aligned with their preference for sequential order. One learner initially hesitated but transformed into confidence once they recognized the structured routine (M5). However, deviations from this logic provoked disorientation and cognitive overload (M3). Neutral learners displayed stable and efficient engagement, facilitated by interfaces that offered clarity, moderate flexibility, and accessible controls (N3). Their satisfaction was not based on interface novelty, but rather on ergonomic balance and consistency. In summary, technology acceptance was contingent upon perceptual alignment. When the interface flow aligned with users' temporal tendencies, engagement increased; when it diverged, dissonance hindered use.

### 3.5.4    Self-Efficacy

Learners' self-efficacy was greatly affected by how well the interface supported their time-based task management strategies. Specifically, monochronic learners gained confidence through routine and predictability. When interfaces offered step-by-step progression and clear task boundaries, these learners' sense of control increased, enabling them to consistently complete tasks (M4). However, disruptions to this flow — such as missing a step or encountering concurrent task models — quickly led to anxiety, revealing their reliance on sequential stability (M3). In contrast, polychronic learners derived efficacy from autonomy and interaction. Mastering multi-module environments and adapting workflows reinforced their sense of competence. As one learner noted, feeling "in control" of the system was empowering, highlighting their need for flexible, responsive structures (P6). Neutral learners benefited from clarity and responsiveness in hybrid layouts. Though less reactive to interface extremes, their confidence depended on steadily progressing with smooth pacing. Even minor usability disruptions, such as disappearing notifications, undermined their confidence (N1). Overall, time orientation was the primary driver of self-efficacy. Interfaces that aligned with learners' time-use logic promoted confidence.

### 3.5.5    Cognitive Load

Cognitive load was significantly influenced by the temporal alignment between the interface design and the learners' information processing rhythms. Much of the cognitive strain did not arise from the difficulty of the content or the complexity of the interface, but from the mismatch between the interface's design and the user's preferred temporal tendency.

Monochronic learners reported a heightened mental load when exposed to visual complexity or overlapping task structures, which disrupted their need for linearity and clear segmentation. These interfaces required users to expend cognitive resources reorganizing disjointed tasks into coherent workflows, as evidenced by reactions to persistent pop-ups and sidebar distractions (M3). Polychronic learners are naturally more adaptable to complexity, but they struggle when systems enforce sequential operations or delayed transitions that disrupt their multitasking flow. In these cases, cognitive effort arose not from volume but from interrupted synchronicity and reduced task fluidity, which led to frustration and disengagement (P1, P3).

By contrast, neutral learners exhibited the lowest cognitive strain, benefiting from interfaces that strike a balance between structure and flexibility. They remained cognitively comfortable as long as the interface preserved a moderate information density and consistent interaction cues. They even tolerated minor imperfections if the pacing remained intuitive (N6). These findings suggest that cognitive load arises from temporal design misalignments, or instances where interface logic fails to mirror users' internalized time-use strategies.

## 4.   DISCUSSION

This study provides compelling evidence that TOPI can significantly enhance learner experience in m-learning by aligning interface logic with individual temporal preferences. Grounded in Person–Environment Fit Theory, which posits that individuals function optimally when their personal characteristics are congruent with environmental affordances [26]. This research reconceptualizes the UI as a digital "environment" and time orientation as a stable psychological "trait." This theoretical framing advances the personalization discourse by shifting the focus from usability to cognitive-temporal alignment, demonstrating that learning outcomes are shaped not only by interface features but also by the compatibility between system pacing and internal temporal schemas.

Supported by both quantitative and qualitative evidence, the findings affirm that user–interface interactions are not merely transactional but are deeply moderated by the temporal congruence between interface behavior and learners' time management logic. Personalized UI design enables users to have meaningful control over their

interaction environment, allowing them to express their personal traits through interface behavior [27]. In this study, time orientation is elevated from a stylistic preference to a core behavioral variable in UI design. Time-oriented elements, such as task mode, layout sequencing, and information density, were found to influence learners' flow and cognitive load directly. This outcome builds upon earlier work on interface personalization [17, 19, 27], which primarily emphasized visual or cognitive-style adaptation. In contrast, the present research establishes temporal alignment as a novel and measurable personalization dimension, integrating temporal cognition into the framework of adaptive interface design.

Empirical patterns across learner groups substantiate this mechanism. Monochronic learners thrived in interfaces with structured workflows, minimalist visuals, and linear progression cues that mirrored their preference for procedural logic and sequential processing. In contrast, polychronic learners engaged more actively with interfaces that supported multitasking, modular organization, and interactive flexibility—features aligned with their nonlinear, parallel cognitive tendencies. These results confirm RQ1 and RQ2, revealing that both polychronic- and monochronic-oriented learners achieve higher acceptance and self-efficacy and experience lower cognitive load when interacting with interfaces designed to reflect their temporal preferences. Neutral learners, often overlooked in binary models, expressed a clear preference for hybrid designs that maintained structural clarity while offering adaptive flexibility. This finding supports RQ3 by demonstrating that neutral learners benefit most from balanced design conditions, aligning with prior observations by Capdeferro et al. [6] that moderate pacing and cognitive equilibrium promote stable engagement. These designs enabled regulated exploration without inducing disorientation or overload, underscoring the importance of cognitive balance over rigid extremes.

From a technology acceptance perspective, temporal alignment influenced not only usability perceptions but also behavioral engagement. Polychronic learners demonstrated curiosity-driven use and exploratory engagement when afforded autonomy and interactivity, while monochronic learners showed conditional acceptance that hinged on structural clarity. In contrast, neutral learners displayed consistent, efficiency-driven interaction, valuing ergonomic balance over novelty. These differentiated patterns support the findings of Davis et al. [28], who claim that interface structure is a decisive factor in shaping user attitudes and

behavioral intentions in technology adoption. However, the study extends this understanding by revealing that acceptance is not solely a response to usability but is dynamically shaped by the degree of temporal fit between system design and individual pacing logic.

The role of personalized interfaces in fostering self-efficacy was also confirmed. Learners across groups reported heightened confidence when the interface aligned with their temporal orientation. Polychronic and monochronic learners, who exhibited stronger temporal preferences, showed greater improvement in self-efficacy when matched with compatible interfaces. In contrast, mismatches led to frustration and doubt, especially when task pacing or layout disrupted their expected control over progression. These findings align with previous studies, which have shown that environmental congruence enhances perceived task ownership and control [29]. This outcome also clarifies the mechanism behind RQ4, illustrating how perceived control and temporal congruence jointly mediate the relationship between interface design and learner confidence—an effect not observed in prior interface-based self-efficacy research [21].

Additionally, cognitive load emerged as a central mediator in the interface–learner interaction. Rather than being driven solely by content complexity or screen layout, cognitive load was shown to stem from temporal incongruence—specifically, when interface pacing and sequencing conflicted with learners' temporal orientation. Monochronic learners experienced a heightened cognitive load when forced to mentally reorganize nonlinear or cluttered interfaces, whereas polychronic learners were strained by overly sequential flows that disrupted their natural synchronicity. In contrast, neutral learners benefitted from balanced visual density and pacing, making them less sensitive to design imperfections. This unintended yet insightful finding among neutral learners revealed a "ceiling effect," wherein high baseline acceptance and efficacy limited measurable improvement. Rather than indicating ineffectiveness, this pattern highlights the stabilizing potential of neutral interface design—paralleling the equilibrium effect reported by Lee et al.[5] and Luo et al. [7] in balanced m-learning environments. These findings reinforce the foundational claims of Cognitive Load Theory, which states that external load is shaped not only by the quantity of information but also by the system–user time alignment.

Importantly, the qualitative findings strongly corroborated the quantitative results:

learners using time-aligned interfaces reported significantly lower cognitive load and higher levels of self-efficacy and technology acceptance. This triangulated evidence reinforces the effectiveness of TOPI and clarifies the mechanisms through which temporal congruence enhances user experience and learning outcomes, addressing RQ4. Unlike previous adaptive m-learning studies, which mainly employed quantitative evaluations of visual or cognitive personalization [5, 15, 18], this study extends the discussion to the underlying mechanisms of temporal alignment. The qualitative insights reveal that perceived temporal fit promotes a stronger sense of control, engagement, and flow, providing explanatory depth that complements the quantitative findings. These insights not only deepen understanding of time-oriented personalization but also inform future interface designs that integrate temporal cognition into adaptive learning systems.

In summary, this research offers a new perspective on personalization in m-learning. By empirically demonstrating that temporal traits significantly influence interaction outcomes, the study suggests a strategic shift from universal UI design to time-aware, adaptive interfaces. Future design frameworks should integrate time orientation as a fundamental dimension of personalization to optimize interactional flow, engagement, and cognitive performance for different learners. Overall, the study successfully fulfills its objectives by addressing the identified research gap and contributes novel evidence that temporal fit constitutes a critical yet previously underexplored determinant of learner–system interaction quality.

## 5. IMPLICATIONS

This study presents several significant implications for the theoretical development of personalized m-learning and the design of educational technologies. First, this study broadens the conceptual landscape of learner-centered education by establishing time orientation as a fundamental construct for personalization. Unlike widely studied traits such as cognitive style or prior knowledge, time orientation reflects the fundamental behavioral patterns and motivational schemas that govern how learners allocate their attention, sequence their tasks, and navigate digital environments. Integrating this temporal dimension into the personalization paradigm provides a new perspective on interface design. It allows designers to align the layout, pacing, and feedback timing with learners' time management tendencies. This extends Person–Environment Fit Theory into the domain of human-computer interaction, empirically

demonstrating that cognitive-affective congruence between user traits and interface behavior improves technology acceptance, self-efficacy, and cognitive efficiency.

Second, the study provides a practical framework for developing TOPI. By mapping the UI preferences of monochronic, polychronic, and neutral learners, it outlines design principles for configuring key elements, such as task sequencing, navigational structure, and information density, according to individual temporal tendencies. These findings support the development of personalized systems that can overcome the limitations of static, one-size-fits-all interfaces. This enables learning platforms to adapt in real time to users' preferred engagement patterns.

Third, the study provides practical guidance for personalized interfaces. Designers can identify users' time orientation and suggest interface designs that align with it. Additionally, implementing toggleable design functions, such as linear or modular task flows and focused or exploratory navigation modes, can empower learners to self-regulate their learning environment, thereby enhancing their motivation and sustained engagement.

Ultimately, this study contributes to the broader goal of inclusive m-learning. Time orientation intersects with cultural norms and diverse learning situations. Thus, designing for temporal fit can support learners with diverse cognitive and contextual backgrounds. This is especially important in asynchronous and lifelong learning contexts, where interface adaptability plays a central role in access, persistence, and learner satisfaction. Together, these implications underscore the necessity of time-oriented personalization in the pursuit of human-centered m-learning design, rather than merely a functional enhancement.

## 6. LIMITATIONS AND DIRECTIONS FOR FUTURE RESEARCH

This study presents novel insights into time-oriented personalization in m-learning. However, several limitations must be considered, which open avenues for future research. It is crucial to acknowledge that these findings originate from a study with a culturally homogeneous sample of Chinese university students. As theorized by Hall [3], time orientation is deeply embedded within cultural norms. The strong preference for structured, monochronic interfaces, for instance, may reflect an educational background that prioritizes sequential and orderly learning processes. Consequently, the TOPI framework and its observed effects may not be

directly generalizable to learners in Western or other cultural contexts where polychronic or multitasking behaviors are more normative. Future research is essential to validate these findings across diverse cultural and educational settings to establish the broader applicability of time-oriented personalization.

Second, the assessment of time orientation relied primarily on self-reported instruments, which, though validated, are vulnerable to subjectivity and social desirability bias. Future studies could incorporate behavioral measurements, such as interaction logs, interface response times, and lag sequential analysis, or even biometric data, such as eye tracking or electroencephalography, to more objectively and dynamically infer temporal cognitive traits.

Third, this study focused on reducing extraneous cognitive load through interface design but did not differentiate between intrinsic and germane load components. Given the layered structure of cognitive load theory, future research should utilize multidimensional cognitive load instruments to assess how temporal interface congruence impacts different types of mental effort in learning tasks of varying complexity.

Fourth, while the present study offers conceptual design guidelines, future work should focus on developing and experimentally validating intelligent interface systems. For example, AI-powered personalization engines that monitor user behavior in real time and dynamically adjust interface elements could serve as testbeds for implementing P–E fit in real educational settings.

In sum, this study establishes a foundational framework for TOPI. However, future research must address cross-cultural scalability, objective measurement, differentiation of cognitive load, intra-individual flexibility, and real-time adaptability to realize its full potential. Improvements in these areas are critical for developing intelligent, temporally sensitive, learner-centered digital learning environments.

## 7. CONCLUSION

This study demonstrates that aligning m-learning interfaces with learners' time orientation significantly improves technology acceptance and self-efficacy and reduces cognitive load. Through a mixed-methods design, the findings revealed that interface congruence with temporal preferences affects learners' engagement and mental effort. Quantitative data confirmed the positive impact of temporal alignment, while qualitative insights clarified how interface structure, pacing, and task flow affect learners' cognitive processing and emotional responses. Monochronic learners performed best with orderly, sequential layouts, polychronic learners responded best to flexible, multitasking environments, and neutral learners preferred balanced, adaptive designs.

These results establish time orientation as a critical dimension of personalized interface design, emphasizing cognitive-affective alignment over generic usability. The study highlights the need for adaptive UI systems that can accommodate diverse temporal profiles, providing a practical foundation for enhancing learner-centered digital education.

## REFERENCES

[1] S. Chopvitayakun, D. Khamsakdee, and N. Aukkanit, "M-Learning Excellence: Personalized Mobile Learning for University Students Via An Android App", Proc. 2023 Int. Conf. Comput. Sci. Comput. Intell. (CSCI), 2023, pp. 1785-1790.

[2] M. L. Bernacki, J. A. Greene, and H. Crompton, "Mobile technology, learning, and achievement: Advances in understanding and measuring the role of mobile technology in education", Contemp. Educ. Psychol., Vol. 60, 2020, Art. no. 101827.

[3] E. T. Hall, "Understanding cultural differences: Germans, French and Americans", Yarmouth: Intercultural Press, 1990.

[4] M. C. Howard and J. E. Cogswell, "A meta-analysis of polychronicity: Applying modern perspectives of multitasking and person-environment fit", Organ. Psychol. Rev., Vol. 13, No. 3, 2023, pp. 315-347.

[5] W. Lee, T. M. K. Tan, and S. S. Hameed, "Polychronicity, the Internet, and the Mass Media: A Singapore Study", J. Comput.-Mediated Commun., Vol. 11, No. 1, 2005, pp. 300–316.

[6] N. Capdeferro, M. Romero, and E. Barberà, "Polychronicity: Review of the literature and a new configuration for the study of this hidden dimension of online learning", Distance Educ., Vol. 35, No. 3, 2014, pp. 294–310.

[7] Y. F. Luo, S. Kang, S. C. Yang, and C. M. Lu, "The relationships among Taiwanese youth's polychronicity, multitasking behavior and perceived learning performance in online learning", Front. Psychol., Vol. 14, 2023, Art. no. 1131765.

[8] A. R. Ikuesan, S. A. Razak, H. S. Venter, and M. Salleh, "Polychronicity tendency-based online

behavioral signature", Int. J. Mach. Learn. Cybern., Vol. 10, 2019, pp. 2103-2118.

[9] G. M. Rose, R. Evaristo, and D. Straub, "Culture and consumer responses to web download time: A four-continent study of mono and polychronism", IEEE Trans. Eng. Manage., Vol. 50, No. 1, 2003, pp. 31-44.

[10] A. Kralisch, M. Eisend, and B. Berendt, "The impact of culture on website navigation behavior", Proc. HCI-Int., 2005, pp. 1-9.

[12] M. Asghar, N. Gull, M. Tayyab, et al., "Polychronicity at work: Work engagement as a mediator of the relationships between job outcomes," Journal of Hospitality and Tourism Management, Vol. 45, 2020, pp. 470–478.

[13] A. M. Neves and L. Morgado, "Monochronic vs. polychronic: A profile of academic time use among online distance education learners," in EDEN Conference Proceedings, No. 1, 2020, pp. 444–453.

[14] J. T. Martins and J. M. B. Nunes, "Polychronicity and multipresence: A grounded theory of e-learning time-awareness as expressed by Portuguese academics' time concepts," in Advances in E-Activities, Information Security and Privacy. 9th WSEAS Int. Conf. on Information Security and Privacy, 2010, pp. 32–40.

[15] T. Alves, J. Natálio, J. Henriques-Calado, and S. Gama, "Incorporating personality in user interface design: A review," Personality and Individual Differences, Vol. 155, 2020, Article 109709.

[16] J. Ming, R. Chen, and R. Tu, "Factors influencing user behavior intention to use mobile library application: A theoretical and empirical research based on grounded theory," Data and Information Management, Vol. 5, No. 1, 2021, pp. 131–146.

[17] R. Heeks, P. J. Wall, and M. Graham, "Pragmatist-critical realism as a development studies research paradigm," Development Studies Research, Vol. 12, No. 1, 2025, Article 2439407.

[18] E. Du Plooy, D. Casteleijn, and D. Franzsen, "Personalized adaptive learning in higher education: A scoping review of key characteristics and impact on academic performance and engagement," Heliyon, Vol. 10, No. 21, 2024.

[19] A. Grogan and J. Lilly, "Everything, everywhere, all at once: A study of polychronicity, work-school facilitation, and emotional exhaustion in working students,"

Frontiers in Psychology, Vol. 14, 2023, Article 976874.

[20] Y. F. Luo, S. C. Yang, and C. M. Lu, "Development of a multidimensional polychronicity scale for information technology learning," Journal of Computer Assisted Learning, Vol. 37, 2021, pp. 387–395.

[21] S. Yorganci, "Investigating students' self-efficacy and attitudes towards the use of mobile learning," Journal of Education and Practice, 2017.

[22] M. T. A. Ghani, M. Hamzah, S. Ramli, W. Ab, A. W. Daud, T. R. M. Romli, and N. N. M. Mokhtar, "A questionnaire-based approach on technology acceptance model for mobile digital game-based learning," Journal of Global Business and Social Entrepreneurship, Vol. 5, No. 14, 2019, pp. 11–21.

[23] S. G. Hart and L. E. Staveland, "Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research," in Advances in Psychology, Vol. 52, 1988, pp. 139–183. North-Holland.

[24] J. Sweller, J. J. van Merriënboer, and F. G. Paas, "Cognitive architecture and instructional design," Educational Psychology Review, Vol. 10, No. 3, 1998, pp. 251–296.

[25] R. E. Mayer and R. Moreno, "Nine ways to reduce cognitive load in multimedia learning," Educational Psychologist, Vol. 38, No. 1, 2003, pp. 43–52.

[26] M. DeJonckheere, L. M. Vaughn, T. G. James, and A. C. Schondelmeyer, "Qualitative thematic analysis in a mixed methods study: Guidelines and considerations for integration," Journal of Mixed Methods Research, Vol. 18, No. 3, 2024, pp. 258–269.

[27] K. Geukes, C. Mesagno, S. J. Hanrahan, and M. Kellmann, "Testing an interactionist perspective on the relationship between personality traits and performance under public pressure," Psychology of Sport and Exercise, Vol. 13, No. 3, 2012, pp. 243–250.

[28] J. M. Davis, L. S. Lee, and M. Y. Yi, "Time-user preference and technology acceptance: Measure development of computer polychronicity," American Journal of Business, Vol. 24, No. 2, 2009, pp. 23–32.

[29] A. Keane, K. Kwon, and J. Kim, "An integrative literature review of person–environment fit and employee engagement," Journal of Management & Organization, Vol. 30, No. 6, 2024, pp. 2149–2178.
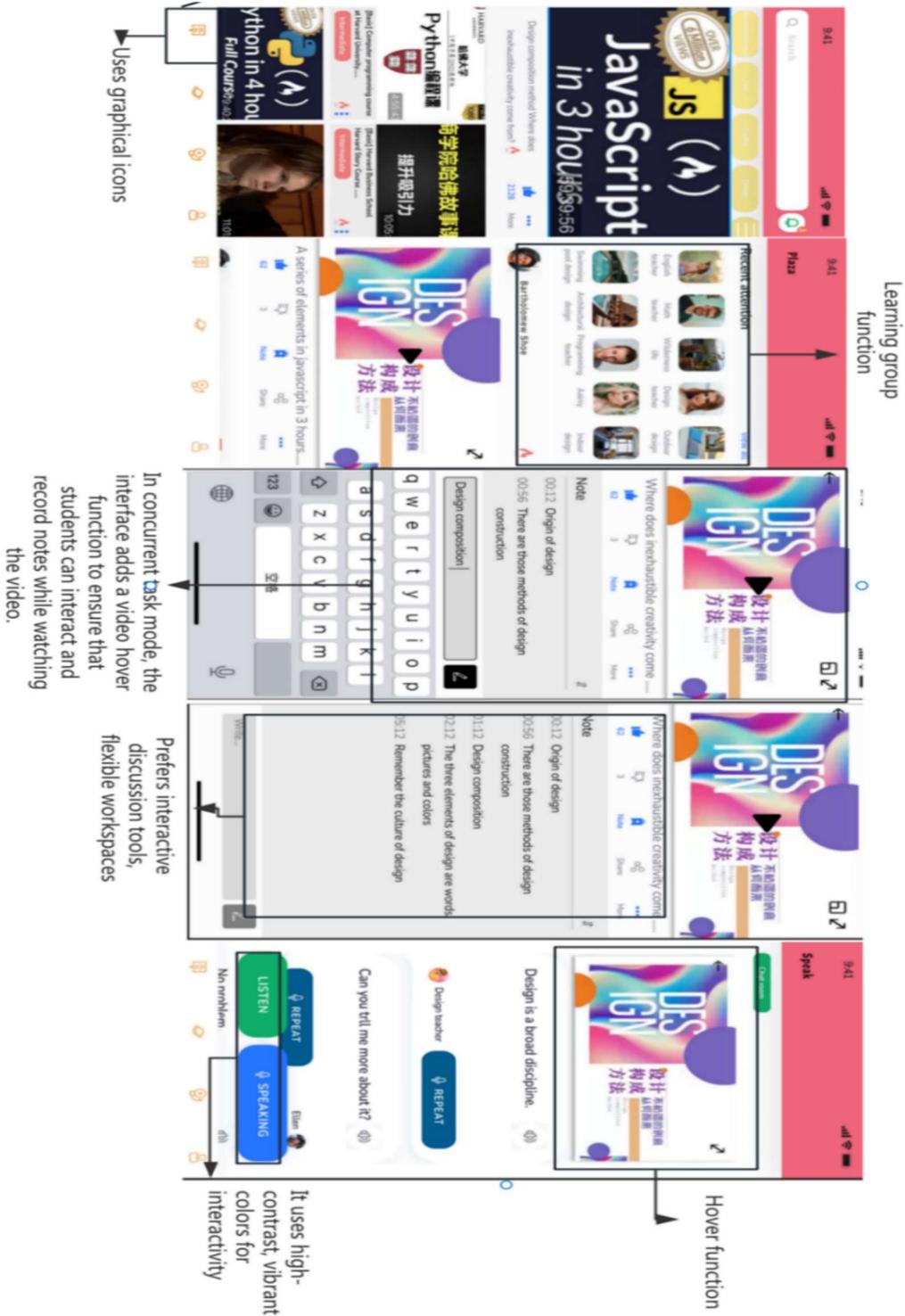
## APPENDICES

### Appendix 1: Interview Questions

1. Can you share how your approach to learning activities reflects your natural time orientation? How does this influence the way you interact with the (polychronic/monochronic/ neutral) interface?

2. In what ways do you feel the design of this interface (e.g., its layout, interaction flow) supports or conflicts with your time orientation preferences? Can you provide specific examples?

3. Please rank the UI elements in sequence according to the degree of satisfaction. You can choose from the following list (Icon style, Color, Information Density, Function, Layout, Interaction Mode, Task Mode, Navigation, Perception of waiting time). How do your preferences for specific UI elements align with your time orientation (polychrons/monochrons/ neutral)?

4. Can you describe your overall experience using this (polychronic/monochronic/ neutral) interface? (Technology acceptance)

5. Which functions did you find particularly easy or difficult to use, and how did they affect your attitude and behavior? (Technology acceptance)

6. How confident do you feel about using this interface to complete your learning tasks? Can you share any experiences that made you feel this way? (Self-Efficacy)

7. In what ways do you think this interface supports or hinders your ability to learn effectively? (Self-Efficacy)

8. Can you describe your experience using this interface in terms of mental effort, physical interaction, time management, task performance, and overall effort?  (Cognitive Load)

9. Were there any moments that felt particularly challenging or frustrating, and how did these aspects affect your ability to complete tasks effectively? (Cognitive Load)

10. Can you describe any problems you encountered using the m-learning system?

11. Tell me more about your preferred learning practices when using m-learning. How do you typically manage your time and learning activities?

**Appendix 2: A more comprehensive overview of the interface design elements and layout for Monochronic Learners**
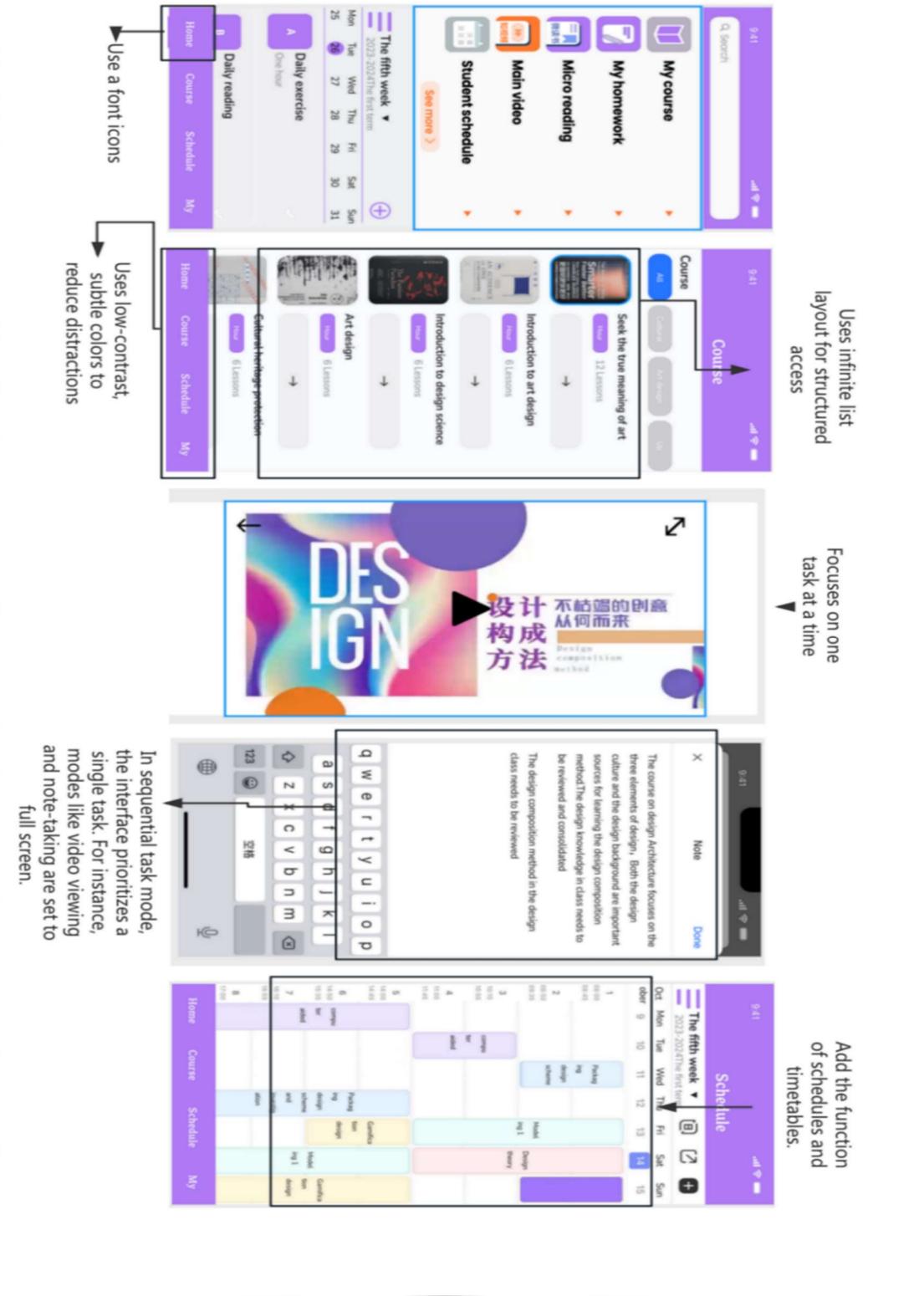
**Appendix 3: A more comprehensive overview of the interface design elements and layout for Polychronic Learners**

**Appendix 4: A more comprehensive overview of the interface design elements and layout for Neutral Learners**