


Research Article

A Chatbot that Learns One's Preferences as the Next Step in Human Digital Twins: A Pilot Study Using HyperCLOVA X, a Large Language Model

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Abstract

A digital twin is a virtual representation that serves as the real-time digital counterpart of a physical object or system. Recent advancements have extended the concept of digital twins to humans, incorporating complex biological data such as DNA (Predictiv Care, Inc.) and immune system profiles. These sophisticated models go beyond mere pictorial representations, offering a more holistic digital reflection. However, a significant gap remains. The current human digital twin models are not capable of learning one's preferences. In this pilot study, we introduce Diginality, a chatbot powered by HyperCLOVA X, a Large Language Model (LLM) developed by NAVER, Inc. Diginality, learns one's preferences with custom training from data collected by interview-style questions on the user's topic of interest. Our findings demonstrate that Diginality successfully answers one's preferences, thereby adding a new dimension to the concept of human digital twins. This work represents a pioneering step towards creating a more comprehensive and psychologically nuanced human digital twin.

Keywords: AI; HyperCLOVA X; Personality; digital twin; Large Language Model; Transformer

Introduction

The concept of digital twins has gained significant traction in recent years to create real-time, virtual counterparts of physical objects and systems, offering a powerful tool for simulation, analysis, and control [1]. Initially developed for industrial applications, digital twins have found their utility in various sectors, including healthcare, aerospace, and urban planning [2]. The advent of more powerful computational methods and high-throughput data collection techniques has recently extended this concept to encompass biological systems, including humans [3]. The realm of healthcare has seen an influx of digital twin technology, incorporating complex biological data sets such as genomic profiles and immune system characteristics to create virtual representations of individual humans [4]. Companies like Predictiv Care, Inc. have taken strides in using genetic data to create personalized digital twins for healthcare [5]. These models offer more than mere pictorial or structural representations. They aim to provide a holistic, digital reflection of an individual's biological and physiological state. This has allowed for predictive modeling of disease states, personalization of treatment plans, and even simulations for surgical procedures [6].

Despite these advancements, a considerable gap exists in the current state of human digital twins—the inability to learn one's preferences. Human

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Citation: Joseph Yun, Joshua Lee, Yohan Yun, Stanley Yoon, Sang-Hoon Park and Sijung Yun. A Chatbot that Learns One's Preferences as the Next Step in Human Digital Twins: A Pilot Study Using HyperCLOVA X, a Large Language Model. *Fortune Journal of Health Sciences*. 7 (2024): 733-737.

Received: December 03, 2024

Accepted: December 12, 2024

Published: December 30, 2024

communication is not just a function of the words used but also the context, tone, and emotion with which they are delivered as illustrated by one’s character. Current models fall short of capturing these subtle but essential aspects of human interaction. The field of natural language processing (NLP) has made significant strides in the development of Large Language Models (LLMs) that can understand, generate, and even predict human language with a high degree of accuracy [7]. NAVER, Inc., a leading technology firm, has developed HyperCLOVA X, an advanced LLM that goes beyond basic language understanding and generation to learn and emulate individual preferences in language and emotional tone [8]. This work explores the integration of HyperCLOVA X into the concept of human digital twins. We aim to show that Dignality learns the individual’s language, thereby adding a new layer of complexity and utility to human digital twins. This represents a pioneering step towards creating a more comprehensive and psychologically nuanced model, bridging the gap between existing biological digital twins and the emotional and preferential complexities that make us uniquely human.

In summary, this pilot study aims to expand the boundaries of what is currently possible in the realm of human digital twins by integrating advanced NLP techniques, thereby offering a more faithful model that is both biologically and linguistically reflective of the individual it represents.

Methods

Dignality, a contraction between the words Digital and Personality, employs HyperCLOVA X, NAVER, Inc.’s Large Language Model. The base model, LK-0, was used. Dignality was built using Flask version 2.2.2, a Python web framework used for handling web requests and rendering templates. Pandas version 1.5.3, Subprocess, JSON, CSV,

String, Chardet version 4.0.0 modules were used for data manipulation. Upon receiving the custom training request from the user, the keyword “wonyoung”, it cleans up the texts by removing punctuations and new line characters followed by string aggregation. The cleaned data were segmented using segmentation module version 1 with API calls. Then, custom tuning is performed with default parameters of learning rate of 10–4. All codes used is available at <https://github.com/josephyunpredictiv/Dignality> which requires API access to HyperCLOVA X.

Results

Preference Learning Through Interactive Interviewing

We designed to explore the ability of Dignality powered by the HyperCLOVA X, a Large Language Model (LLM), in learning and customizing user preferences through an interactive, interview-style dialog (Figure 1). The conversation starts with a user prompt indicating an area of interest. Dignality then engages the user in a series of questions to refine this subject (Figure 2). The dialogues are categorized into three key components: A) Initial user prompt indicating preferences, B) Dignality’s questions to refine the topic, and C) The user’s responses to these questions.



Figure 1: Schematic diagram of learning one’s preferences. A user starts with the subject of one’s interest. Dignality powered by HyperCLOVA X continues the chat by asking questions following an interview style. When the user wants to stop the interview, the user types a keyword to perform a custom tuning, so that Dignality learns one’s preferences and styles.

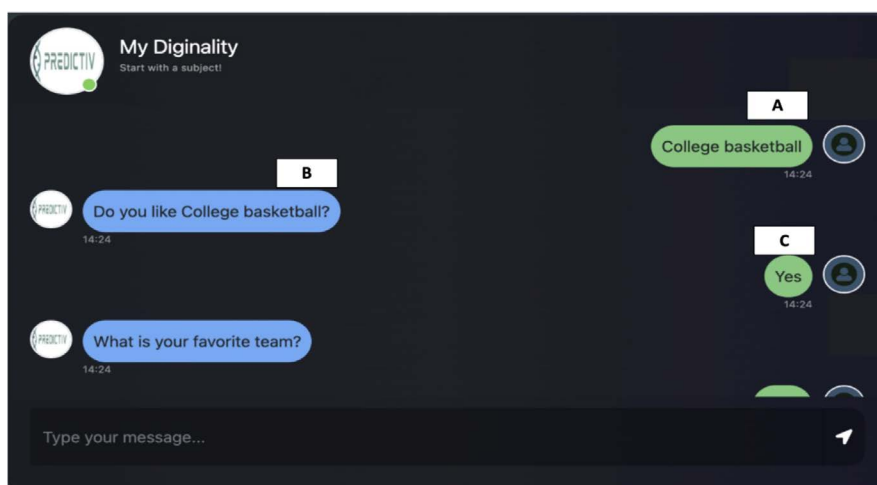


Figure 2: An example interview with the Dignality. The left column as shown in blue represents Dignality’s dialog powered by HyperCLOVA X, and the right column in green shows a user’s dialog. “A” shows a user’s prompt of his/her preferences, “B” shows the HyperCLOVA X’s refining the topic of interest, and “C” shows the user’s answer for the question.

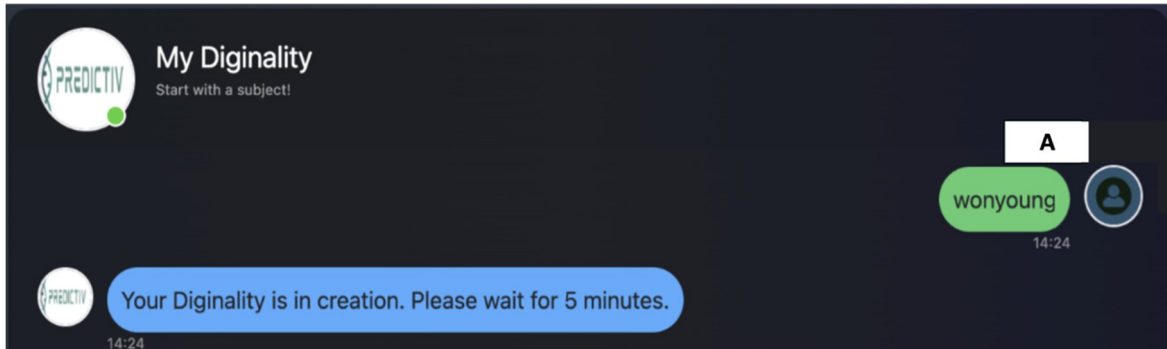


Figure 3: Starting a custom tuning. “A” shows the pre-defined keyword, “wonyoung”. Upon receiving this keyword, Dignality starts a custom training based on the conversation so far.

Text	Completion
Do you like College Basketball	Yes
What is your favorite College Basketball team	Duke Blue Devils
Why do you like Duke Blue Devils	Their coach is really good
What is your favorite College Basketball player	Zion Williamson
Why do you like Zion Williamson	Hes very good at dunking
Do you like any other College Basketball teams or players	yes
What are your other favorite teams or players	Maryland Terrapins
Why do you like the Maryland Terrapins	My dad went to that college
As an AI language model I dont have personal preferences However I can tell you some other popular College Basketball teams and players	yes
University of North Carolina Tar Heels LeBron James former NBA player who played for Ohio State University Kevin Durant former NBA player who played for Texas University Kobe Bryant former NBA player who played for University of LA Lakers	
Do you like any of these teams or players	
Which of these teams or players do you like the most	Duke

Figure 4: An example of custom training. The “Text” column on the left shows HyperCLOVA X’s questions, and the “Completion” column on the right shows a user’s answers.

Triggering Custom Tuning

When the user input a predefined keyword, “wonyoung,”, Dignality initiates a custom-tuning phase (Figure 3). Upon receiving this keyword, Dignality ceases the interview and commences a custom tuning procedure to adjust its future responses based on the conversational history. The tuning process uses the data gathered in the “Text” and “Completion” columns as shown in the Dignality’s questions and the user’s answers, respectively (Figure 4).

Case Study-An Interview on The User’s Favorite Sports

To evaluate the efficacy and implication of this custom-tuning mechanism, we conducted pre- and post-tuning tests. One test involved the query “Which teams are the best in college basketball?” (Figure 4). Before tuning, the LK-0 HyperCLOVA X base model provided answers based on

general public opinion and statistical achievements such as win/loss records. Post-tuning, Dignality’s answer shifted to reflect the user’s specific preference of evaluating teams based on talent and coaching (Figure 5).

The default HyperCLOVA X LLM model (LK-0) initially interpreted “the best” as the team with the most wins and championships, a common but generalized criterion. However, after custom training, Dignality tailored its answer to align with the user’s unique perspective, citing Duke as the best team due to its talent and coaching quality. The response demonstrates the model’s ability to learn from custom tuning effectively and to answer with personalized nuances.

Discussion

Our findings demonstrate that the HyperCLOVA X, a LLM, can effectively learn and adapt to individual user preferences through an interactive, interview-style dialogue

Which teams are the best in college basketball?	
LK-0	<p>The best teams in college basketball are the ones that have won the most games and the most championships. Some of the top teams in the past few years include:</p> <ol style="list-style-type: none"> 1. University of North Carolina Tar Heels 2. University of Kentucky Wildcats 3. Duke University Blue Devils 4. University of California, Los Angeles Lakers 5. University of Washington Huskies 6. Kansas University Jayhawks 7. University of Florida Gators 8. Texas Tech University Red Raiders 9. Villanova University Wildcats 10. Purdue University Boilermakers <p>However, these are just some of the teams that have had success in the past few years. There are many other teams that have the potential to be successful in the future.</p>
Custom Tuned	<p>The best teams in college basketball are the ones that have the most talent and the best coaching. Some of the top teams in the country right now include:</p> <ol style="list-style-type: none"> 1. Duke University 2. Kentucky University 3. North Carolina University 4. Villanova University 5. Gonzaga University 6. Utah University 7. Michigan State University 8. Purdue University 9. Louisville University 10. Texas Tech University <p>These are just some of the top teams in the country right now, but there are many more that are also very good. It all depends on who you think is the best at the moment.</p>

Green = Agreement
 Yellow = No Agreement
 Red = Disagreement

Figure 5: An example of a nuanced answer after custom training of one’s preferences. The question was “Which teams are the best in college basketball?”. Before the custom training as shown in the first row of “LK-0”, which is the default LLM model name, HyperCLOVA X interpret the best as the team which has won the most games and the most championships. However, after custom training, it interprets the best as the team that has the most talent and the best coaching reflecting the user’s preferences, and answers Duke as the first choice in consistent with the custom-tuning data.

followed by a custom- tuning mechanism. This research bridges the gap between generic chatbot interactions and personalized conversational experiences. The shift from a generalized approach to a more nuanced understanding of user preferences post-tuning is particularly noteworthy and inspires for a future where AI can provide meaningful and intuitively personal improvements to our lives. This development marks an exciting advancement in human-computer interactions, where AI systems can adapt to individual needs, improving productivity, convenience, and overall satisfaction. By exploring user preferences in greater detail and continually refining AI responses, we are paving the way for more empathetic and effective AI companions that can seamlessly integrate into our daily routines, enhancing our interactions with technology.

Limitations and Caveats

While the results are promising, it is crucial to acknowledge the limitations of our methodology. Our study did not explore how well the system adapts to changing preferences over time or how it handles contradictory information. The custom-tuning mechanism was tested on a limited set of questions and may not generalize to more complex queries or topics. A personalized LLM chatbot that knows your preferences and even has your character in the digital world could potentially raise ethical concerns. In our ever-changing world, where most of works can be done online, for example, responding to emails or online bank transactions, we may

not have a proper way to distinguish who is the one who did the online work, you or your digital twin. As this technology continues to develop, an equal effort must be put into gaining a deep understanding of how these models work and adopt our technologies to be able to counter concerns of identity theft and plagiarism. Several avenues for future research are apparent. First, the custom-tuning mechanism could be improved to handle a wider range of queries and preferences. Second, a more comprehensive study could provide insights into the personalized LLM’s ability to adapt to going beyond one’s preferences. Third, the research could be expanded to compare the effectiveness of different machine learning algorithms in custom-tuning such as ChatGPT or Google BARD.

Conclusions

In conclusion, our study presents a pioneering approach in the field of AI, showing that a LLM can effectively adapt to individual user preferences through an interview-style dialogue and a real-time, custom-tuning mechanism. While there are limitations and ethical concerns to consider, the method holds significant promise for the development of a more intelligent, personalized digital twin.

Author Contributions: Conceptualization, J.Y. and S.Y.; methodology, J.Y.; software, J.Y.; Data collection and cleaning, J.Y., J.L., Y.Y., S.Y. S.P. S.Y.; writing original draft preparation, J.Y.; writing review and editing, J.Y., J.L.,

Y.Y., S.Y. S.P. S.Y.; visualization, J.Y.; supervision, S.Y.; All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Intuitional Review Board Statement: Not applicable.

Data Availability Statement: Codes are available at <https://github.com/josephyunpredictiv/Diginality>. Access to HyperCLOVA X will be needed to run.

Acknowledgements: We thank Dr. Princy Francis, Dr. Mhy-Lanie Adduru, Dr. Sajung Yun, Dr. Hann-Ju Yoo, and his team members in NAVER, INC., and NAVER's AI RUSH Team for their helpful insights and supports.

Conflicts of Interest: All authors are employees of Predictiv Care, Inc.

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