

Chatbots and Socio-Emotional Cues in Corporate E-Learning: Evidence on Learning and Dropout

CHATBOTS Y SEÑALES SOCIOEMOCIONALES EN EL APRENDIZAJE ELECTRÓNICO CORPORATIVO: EVIDENCIA SOBRE EL APRENDIZAJE Y EL ABANDONO

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Abstract

Purpose: This study examined whether instructional chatbots and emojis improved learning outcomes and reduced dropout in asynchronous corporate training. It also explored participant performance profiles through agent-based simulation.

Methodology: The study followed three phases: chatbot development, implementation of a four-week private online course using a 2×2 factorial experiment (chatbot: yes/no \times emojis: yes/no), and simulation in NetLogo. A total of 120 employees were evenly assigned to four experimental conditions.

Results: Chatbot use and emoji presence were associated with better learning outcomes and lower dropout. The chatbot-plus-emoji condition showed the highest survival rates (68%–76%) and the lowest dropout risk (24%–32%). Posttest scores indicated significant retention after 15 days ($\Delta = 6.61$, $p < 0.001$). The simulation reproduced the empirical ranking of the conditions and identified a high-performing profile characterized by prior experience with virtual training, longer organizational tenure, familiarity with podcasts, and stable weekly study time.

Implications: The findings indicate that combining cognitive support through chatbots with socio-emotional signaling through emojis can strengthen persistence in corporate e-learning.

Originality: This study integrates factorial experimentation and agent-based simulation to explain how expressive digital interactions support learning continuity.

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Resumen

Propósito: Este estudio examinó si los chatbots instruccionales y los emojis mejoraron el aprendizaje y redujeron la deserción en una capacitación corporativa asincrónica. Además, exploró perfiles de rendimiento mediante simulación basada en agentes.

Metodología: El estudio siguió tres fases: desarrollo del chatbot, implementación de un curso privado en línea de cuatro semanas mediante un experimento factorial 2×2 (chatbot: sí/no \times emojis: sí/no), y simulación en NetLogo. Participaron 120 empleados asignados equitativamente a cuatro condiciones experimentales.

Resultados: El chatbot y los emojis se asociaron con mejores resultados de aprendizaje y menor deserción. La condición chatbot más emojis mostró la mayor supervivencia (68%–76%) y el menor riesgo de abandono (24%–32%). El posttest evidenció retención significativa a los 15 días ($\Delta = 6.61$, $p < 0.001$). La simulación reprodujo el orden empírico de las condiciones e identificó un perfil de alto rendimiento con experiencia previa en formación virtual, mayor permanencia organizacional, familiaridad con pódcast y tiempo semanal estable de estudio.

Implicaciones: Los resultados indican que la combinación de apoyo cognitivo mediante chatbots y señalización socioemocional mediante emojis puede fortalecer la persistencia en el aprendizaje electrónico corporativo.

Originalidad: Este estudio integra experimentación factorial y simulación basada en agentes para explicar cómo las interacciones digitales expresivas favorecen la continuidad del aprendizaje.

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INTRODUCTION

Corporate training is essential for improving worker performance, boosting motivation, and driving organizational effectiveness. However, as companies expand geographically and adopt flexible work models, traditional in-person training is increasingly challenged by logistical and economic constraints. In response, organizations have shifted toward virtual training formats to enable large-scale, asynchronous participation. Despite these advantages, online training environments often experience lower engagement and higher dropout rates, particularly among employees who work independently or at dispersed field locations.

Within this context, conversational agents have emerged as a promising tool for sustaining engagement in digital learning. Chatbots provide real-time guidance, answer questions, and structure course progression, functioning as adaptive instructional assistants. Prior

studies grounded in the Technology Acceptance Model (TAM) indicate that perceived usefulness and ease of use are key drivers of adoption and continued engagement (Ben Ammar & Neji, 2021; Sun et al., 2022; Yin et al., 2023). These findings suggest that chatbots can serve as effective cognitive scaffolds, reducing uncertainty in the learning process and empowering learners to manage tasks more effectively.

However, functional support alone is insufficient to ensure persistence in digital environments, which are also shaped by perceptions of interpersonal connection and social presence. The absence of expressive cues can heighten psychological distance and weaken commitment to coursework (Lowenthal & Borup, 2020). From this perspective, socio-emotional markers, such as emojis, may reduce the impersonal nature of text-based communication. Drawing on Social Presence Theory (Garrison et al., 2000), prior research shows that emojis enhance

perceived warmth and relational closeness (Li et al., 2019; Kaye et al., 2021), which, in turn, supports satisfaction and continuity in learning processes (Park et al., 2022a). Incorporating socio-emotional cues into chatbot interactions may therefore strengthen the learner's sense of accompaniment, particularly in asynchronous corporate training.

Systematic reviews have documented the growing use of chatbots in educational contexts, although evidence regarding their combined role with socio-emotional cues in corporate settings remains limited (Quiroga-Pérez et al., 2020). This gap constrains our understanding of how cognitive and socio-emotional digital supports interact to influence learning performance and dropout.

To address this gap, this study investigates how integrating a chatbot and socio-emotional cues (emojis) influences learning outcomes and persistence in a corporate virtual training program for geographically dispersed employees. Furthermore, the study incorporates an agent-based simulation to model learning efficiency and dropout patterns under the same experimental conditions, thereby extending the empirical findings through computational analysis. This dual approach provides a more comprehensive understanding of how expressive, adaptive digital tools can enhance continuity in corporate e-learning environments.

METHODOLOGY

The study employed an experimental design complemented by an agent-based simulation model. The methodological process unfolded in three sequential phases to ensure coherence between empirical data and computational validation. The first phase involved designing and developing the chatbot used in the intervention. The development process followed principles of conversational personality, response typology, and visual expressiveness appropriate for educational conversational agents, consistent with prior work showing that users respond to distinct text-based chatbot personality cues (Ruane et al., 2021). This phase ensured that the chatbot could deliver instructional guidance and respond coherently to learner inquiries, an

interactional requirement that has also been highlighted in prior work on multi-turn chatbot coherence (Suhaas Kiran et al., 2021; Mohd-Zukhi et al., 2020).

The second phase involved a four-week, asynchronous SPOC delivered via Moodle; participants completed a pretest assessing their initial knowledge and baseline perceptions of chatbot usability. The study employed a 2×2 between-subjects factorial design, manipulating two independent variables: chatbot use (present or absent) and emoji presence (present or absent). Eligible participants were block-assigned to one of four equally sized groups to ensure comparable initial knowledge: chatbot with emojis, chatbot without emojis, emojis without chatbot, and a control group without chatbot or emojis. The dependent variables were weekly learning performance and dropout during the training period, fifteen days after course completion, a post-test assessed learning retention and changes in perceived usability. Persistence throughout the course was examined using survival analysis to determine the weekly dropout risk associated with each experimental condition.

The third phase involved developing an agent-based simulation in NetLogo to model learning efficiency, dropout behavior, and perceived human-machine interaction. The simulation agents were parametrized using the sociodemographic characteristics, digital readiness indicators, and learning trajectories observed in the empirical phase. Learning efficiency was operationalized through a simplified artificial neural network structure adapted from Sancho's (2018) NetLogo-based proposal for modeling neural computation. This reference was used as a computational framework rather than as a substantive theory of learning. Specifically, the model represented each agent's learning process through input parameters derived from the empirical phase, including prior digital readiness, study time, previous virtual training experience, and interaction with the chatbot and emoji conditions. Variability in the hidden layer was incorporated to represent heterogeneity in cognitive processing across agents. Each factorial condition was replicated as a distinct simulation environment. During the simulated training, chatbot interactions were modeled using the same instructional and socio-emotional cues implemented in the experiment,

including positive and corrective feedback conveyed through emojis. This design enabled the simulation to reproduce the behavioral dynamics observed in the SPOC and to assess the consistency of these patterns across 1,500 iterations per condition.

The study received formal authorization from the company's training department. All participants provided informed consent prior to data collection, and the research team anonymized all records in accordance with institutional data protection procedures. The integration of experimental data with computational modeling enhanced the study's internal validity and provided additional evidence on the behavioral mechanisms driving persistence and learning in corporate virtual training. Accordingly, the findings should be interpreted within the context of a single organizational setting and a specific corporate training program, which limits direct generalization to other industries or institutional contexts.

Instruments

The study used two instruments to evaluate learning and the technological interaction experience. The first instrument measured participants' initial technological readiness and was based on the UTAUT model's constructs of performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2013). This version, previously validated in Colombian organizational environments (Cortés et al., 2020), demonstrated adequate internal consistency in the present study ($\alpha = 0.78$ for clarity and $\alpha = 0.88$ for coherence). The instrument established participants' baseline familiarity with digital learning environments and contextualized subsequent changes in learning and persistence.

The second instrument assessed the chatbot's usability, adaptability, and functionality using a scale adapted from Tariverdiyeva and Borsci (2019). The research team conducted internal validation using an Exploratory Factor Analysis with Varimax rotation. The sample demonstrated sufficient adequacy ($KMO = 0.69$), and Bartlett's test confirmed factorability ($\chi^2(3, N = 203) = 586.45, p < 0.001$). The final factor solution retained three dimensions,

accounting for 88.69% of the total variance, and included nine items with loadings above 0.40 and communalities greater than 0.35. The instrument demonstrated strong internal consistency ($\alpha = 0.84$), confirming its suitability for assessing the interaction experience during the SPOC.

In alignment with the study's theoretical framework, the UTAUT-based diagnostic served solely to establish a baseline of participants' initial technological readiness. In contrast, the interpretation of learning and persistence was guided by the Technology Acceptance Model and Social Presence Theory. These models provide the conceptual foundation for understanding how perceived usefulness, ease of use, and socio-emotional cues collectively influence motivation and continuity in virtual learning environments.

Participants

The study recruited 323 employees from a Colombian hydrocarbon services company via digital invitations over three months, ensuring a homogeneous organizational context. A total of 90.8% completed the pretest and met the eligibility requirements. The sample exhibited balanced gender representation (48.3% women; 51.7% men) and diverse educational backgrounds, ranging from technical vocational training (46.7%), high school (10.8%) to postgraduate studies (9.2%). Participants worked in various operational areas operations (39.2%), administrative services (23.3%), and HSEQ (4.2%) and reported varying levels of prior training experience: 19.2% had attended classroom-based courses, 10.8% had taken virtual courses, and 3.3% had participated in both modalities.

From this pool, 120 individuals who met the inclusion criteria-completing the pretest, maintaining enrollment, and possessing the technical ability to access the mobile-based SPOC- progressed to the experimental phase. The research team applied block randomization to assign participants evenly across the four conditions of the 2x2 factorial design, ensuring comparable baseline knowledge among groups. Each condition included 30 participants: chatbot

+ emojis, chatbot only, emojis only, and control (no chatbot/no emojis). Before the intervention, participants also reported their previous SPOC experience, which spanned entrepreneurship (25%), education (40%), science (22.5%), and finance (7.5%), enabling the research team to characterize their familiarity with asynchronous learning. Although the sample was drawn from a single company, its internal diversity, demographics, and prior training experiences supported robust experimental comparisons, while acknowledging inherent limits to external generalization.

Data Collection

Data were collected during a four-week corporate SPOC delivered on the Moodle platform. A total of 323 employees registered for the course; however, only 120 met the predefined inclusion criteria: current company affiliation, access to an internet-enabled mobile device, and completion of all preliminary training steps. These criteria ensured that the dataset represented individuals fully equipped to engage with the digital training environment. Fifteen days before the course, these participants completed a mobile-based pretest assessing baseline knowledge and initial perceptions of chatbot usability. The course consisted of four asynchronous modules released weekly to all participants. Following the pretest, eligible participants were randomly assigned to one of four balanced experimental conditions defined by the 2×2 factorial design crossing chatbot use (yes/no) and emoji presence (yes/no). All groups received the same instructional content, delivery schedule, and weekly assessments.

Participants' engagement was tracked weekly. At the end of each week, they completed a short content-based quiz, which served as the operational measure of continued participation. A participant was classified as a dropout in the first week if they failed to submit the quiz and did not engage in any subsequent activity, allowing precise identification of the time-to-dropout for survival analysis. This operationalization supported the use of Kaplan-Meier estimators and Cox proportional hazards models to analyze weekly persistence patterns. Fifteen days after completing the final module, participants completed a post-test containing the same knowledge items as

the pretest to evaluate retention. During this phase, participants in the chatbot conditions also completed a scale assessing usability, adaptability, and functionality, which was adapted from Tariverdiyeva and Borsci (2019). The individual learning trajectories and dropout behaviors recorded throughout the course informed a subsequent agent-based simulation in NetLogo that replicated the four experimental conditions and modeled learning efficiency and dropout dynamics. All procedures adhered to institutional data protection guidelines, and participants provided informed consent before enrollment.

RESULTS

Experimental Phase: Effects on Learning

Learning outcomes, measured across the four instructional modules, were analyzed using a Univariate General Linear Model. The model satisfied all necessary statistical assumptions, ensuring the validity of the factorial comparisons. Statistical results are reported using standard notation: M denotes the mean, SD the standard deviation, Δ the mean difference between two measurements, CI the confidence interval, t the Student's t statistic, F the analysis-of-variance statistic, χ^2 the chi-square statistic, p the probability value, and η^2_p the partial eta-squared effect size.

Baseline knowledge, assessed via a pretest before the intervention, revealed an intermediate level of initial proficiency across the four topics on a five-point scale. Participants showed the highest familiarity with Topic 1 ($M = 3.93$, $SD = 0.86$) and Topic 2 ($M = 4.05$, $SD = 0.84$), and the lowest with Topic 3 ($M = 3.29$, $SD = 0.88$) and Topic 4 ($M = 3.07$, $SD = 1.08$). These results suggest greater familiarity with the competencies addressed in Topic 2 and lower familiarity with the skills required for Topic 4.

Analysis of the weekly learning assessments revealed apparent differences between the factorial conditions. Participants assigned to the chatbot conditions consistently outperformed those without chatbot support. Furthermore, the presence of emojis also positively affected learning performance, regardless of the chatbot's presence. These initial descriptive trends were subsequently examined and

supported by the factorial analysis presented in the following subsection.

Experimental Phase: 2×2 Factorial Analysis

Learning performance was calculated as the mean score across weekly assessment, each measured on a five-point scale. A 2×2 factorial ANOVA evaluated the independent and combined effects of chatbot use (yes/no) and emoji presence (yes/no). The corrected model was significant, $F(3, 83) = 9.94$, $p < 0.001$, $\eta^2p = 0.11$, confirming that the experimental conditions collectively explained a meaningful proportion of the variance in learning outcomes. The main effect of chatbot use was significant, $F(1, 83) = 19.48$, $p < 0.001$, $\eta^2p = 0.25$, indicating that participants who interacted with the chatbot achieved higher learning scores. Emoji presence also exerted a significant main effect, $F(1, 83) = 7.70$, $p < 0.01$, $\eta^2p = 0.09$, demonstrating that socio-emotional cues contributed positively to learning.

The interaction between chatbot use and emoji presence was statistically significant ($p = 0.013$). This pattern suggests that the combination of both elements improved learning outcomes within the experimental conditions. The chatbot primarily functioned as a cognitive guide, while the emojis provided complementary socio-emotional reinforcement. This independent pattern aligns with the Technology Acceptance Model: perceived usefulness increased through the chatbot's instructional support, whereas perceived ease of communication and emotional clarity increased through emoji-based signaling. Together, these distinct yet complementary mechanisms appear to have enhanced the user experience and were associated with higher learning outcomes.

To identify additional predictors of course approval within each experimental condition, a logistic regression was conducted with approval as the dependent variable (0 = failed; 1 = passed). In the chatbot condition, the week of dropout was the only covariate that significantly contributed to the model. In Block 0, the baseline approval rate was 56.7%. In Block 1, the omnibus test indicated that the model was significant and that including dropout week improved prediction accuracy, $\chi^2(1, N = 30) = 30.49$, $p = 0.001$. The model accounted for 85.6%

of the variance of the approval (R^2 Nagelkerke = 0.86). The classification table showed 93.3% accuracy when the dropout week was included. Dropout week significantly predicted approval ($p = 0.02$), with $\text{Exp}(B) = 23.03$, indicating that participants who persisted longer in the course had a substantially higher likelihood of passing.

In the emojis condition, the number of prior courses completed was the only significant covariate. In Block 0, the baseline approval probability was 60%. In Block 1, the omnibus test indicated that including this covariate significantly improved the model, $\chi^2(1, N = 30) = 30.46$, $p = 0.001$. The model accounted for 86.1% of the variance (R^2 Nagelkerke = 0.86), and classification accuracy reached 93.3% when the number of prior courses was included. This covariate significantly predicted approval ($p = 0.02$), with $\text{Exp}(B) = 19.29$, suggesting that participants with greater prior training experience were substantially more likely to pass the course.

Survival Phase

A survival analysis was conducted to evaluate the time until dropout over the four-week training period. Dropout was operationally defined as the week in which a participant failed to submit the weekly assessment and did not return in subsequent weeks. This time-to-event approach was chosen because the critical outcome was the timing of withdrawal, not merely its occurrence. The dependent variable was the number of weeks of continued participation (0–4), and the event was defined as abandonment of the course.

The mean duration of participation varied across experimental conditions. The chatbot + emojis group demonstrated the highest persistence ($M = 3.42$, $SD = 0.81$), followed by the chatbot-only group ($M = 3.11$, $SD = 0.94$). The emojis-only group remained engaged for a shorter period ($M = 2.78$, $SD = 1.02$), while the control group exhibited the lowest persistence ($M = 2.36$, $SD = 1.21$). These descriptive trends were consistent with the survival curves, showing that the combination of cognitive support (chatbot) and socio-emotional cues (emojis) yielded the most sustained engagement.

The Kaplan–Meier estimator revealed that attrition was the highest during the first

week, with 31% of registered participants discontinuing the program. The overall median survival time was four weeks, indicating that half of the sample had disengaged by the course's conclusion. The hazard function revealed that risk peaked in Week 1 (36%), a pattern consistent with the early-stage attrition commonly observed in self-paced digital training.

When analyzed by factorial condition, the chatbot + emojis group achieved the highest cumulative survival (68–76%) and the lowest dropout risk (24–32%). In contrast, the control group (no chatbot, no emojis) had the lowest survival (42–58%) and the highest abandonment hazard (0.68–0.84). These results provide evidence suggesting that pairing instructional assistance with socio-emotional cues was associated with lower early disengagement during the training period.

The Cox proportional hazards models identified specific covariates associated with dropout risk. Among participants in the chatbot conditions, prior podcast exposure was associated with reduced hazard. The model was significant, Wald $\chi^2(1, N = 30) = 14.29$, $p < 0.01$, with $\beta = -0.09$, indicating that participants without podcast experience had a 9% higher likelihood of dropping out. In the emojis conditions, previous participation in virtual training reduced the probability of abandonment. This model was also significant, Wald $\chi^2(1, N = 30) = 18.42$, $p < 0.01$, with $\beta = -0.27$, reflecting a 27.7% higher dropout risk among participants without prior online training experience. Overall, the survival analysis showed that integrating cognitive support and socio-emotional signaling was associated with reduced dropout risk across the four-week SPOC.

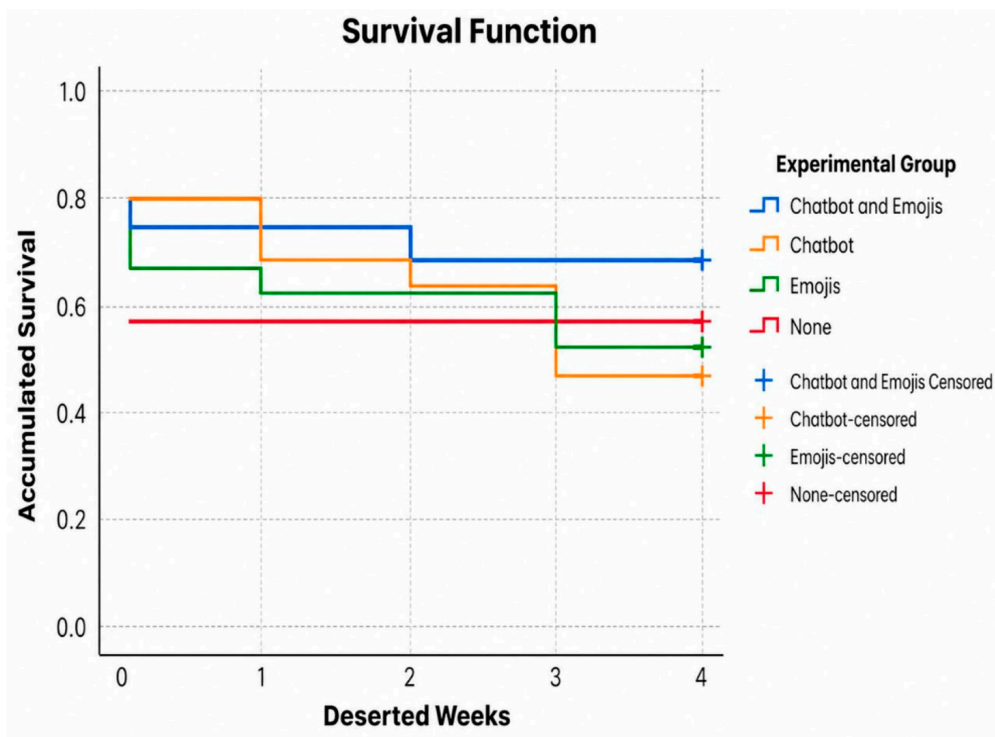


Figure 1. Kaplan–Meier Survival Curves for Course Persistence Across the Four Experimental Conditions. Source: Own elaboration.

Learning Retention (Post-Test Phase).

The post-test results, administered 15 days after the course, showed consistent and statistically significant improvements in learning. Compared to baseline, mean post-test scores increased by 0.30, 0.37, 0.64, and 0.82 points across the four topics on the five-point scale.

The global comparison between pretest and post-test scores revealed a statistically significant improvement from $M = 51.01$ ($SD = 5.91$) to $M = 57.62$ ($SD = 6.47$). This gain of $\Delta = 6.61$ points was statistically significant, with a 95% CI of [5.33, 7.89], $t(119) = 10.24$, $p < 0.001$. These results indicate that participants acquired the training content and retained it over the post-intervention period.

Participants assigned to the chatbot conditions reported a significant increase in the perceived usability of the tool, with scores rising from $M = 48.97$ ($SD = 3.57$) at the beginning of the program to $M = 53.53$ ($SD = 2.21$) in the post-test, $\Delta = 4.56$, 95% CI [3.19, 5.92], $t(35) = 6.77$, $p < 0.001$. This upward trend indicates that interaction with the chatbot became more intuitive and more efficient for users over time. The integration of the chatbot's instructional scaffolding with the socio-emotional cues provided by emojis strengthened learners' overall perception of technological support, fostering a more positive and supportive learning experience.

Agent-based simulation phase

An agent-based simulation modeled learning efficiency, dropout behavior, and human-machine interaction across the four experimental conditions of the 2×2 factorial design (chatbot \pm / emojis \pm). The model was programmed in NetLogo and parametrized the agents based on sociodemographic characteristics, prior digital readiness, and learning trajectories observed in the empirical phases. This parametrization allowed the agents to replicate behavioral tendencies documented during the SPOC.

Learning performance was operationalized using an artificial neural network architecture adapted from Sancho's (2018) proposal, incorporating stochastic variation in the hidden layer to simulate heterogeneity in cognitive processing. The model executed 1,500 iterations for each factorial condition to generate a

sufficiently large synthetic dataset representing learning outcomes, dropout patterns, and measures of usability, adaptability, and functionality.

The simulation outputs were processed in Orange and grouped into four clusters corresponding to the four experimental configurations. The mean learning scores in clusters C1–C4 mirrored the performance patterns observed empirically. The chatbot + emoji configuration produced the highest overall mean ($M = 4.43$, $SD = 2.79$), followed by the chatbot-only configuration ($M = 4.42$, $SD = 2.81$). The emoji-only configuration and the control (no chatbot/no emojis) showed slightly lower means ($M = 4.42$, $SD = 2.80$; $M = 4.41$, $SD = 2.78$), maintaining the same performance hierarchy observed in the experiment. The simulation further indicated that agents required a minimum usability, adaptability, and functionality score of 4 on a seven-point scale for the chatbot to impact learning positively. This threshold is aligned with the empirical findings, demonstrating that the model successfully replicated conditions under which interactions were sufficiently clear, responsive, and supportive.

Dropout behavior in the simulation mirrored the same comparative pattern observed experimentally, although absolute levels were lower. Cluster 3, representing the chatbot + emoji condition, again showed the highest learning means. The configuration without a chatbot or emojis exhibited the lowest learning and one of the highest simulated dropout rates. Although the model generated lower dropout magnitudes than those observed in the actual training program, particularly for the control group the relative ordering remained consistent. This alignment indicates that the simulation functioned as an analytical model rather than as an exploratory mechanism.

The visualizations generated in Orange further strengthened the model's internal validity. The cluster map revealed substantial internal similarity among C2, C3, and C4, whereas C1 showed more atypical configurations. The self-organizing map clearly separated the four clusters, with node sizes reflecting convergence frequency across the 1,500 iterations. The distance map highlighted dense blue regions representing minimal intra-cluster distance, and isolated red and yellow zones corresponding

to atypical or transitional parameter combinations. These patterns confirmed that the simulation generated stable behavioral regimes and that transitions between parameter configurations produced predictable shifts in learning outcomes and dropout probabilities.

Additional graphical analyses supported the robustness of the model. Boxplots for each cluster revealed left-skewed distributions, with most simulated scores slightly below the means—mirroring the empirical distribution of learning performance. The Sieve diagram indicated statistical independence between clusters and the categorized global learning mean ($\chi^2(9, N = 1500) = 12.94, p = 0.16$), while highlighting deviations consistent with empirical findings, such as the lower-than-expected frequency of low scores within the chatbot + emoji cluster. Scatter plots and t-SNE embeddings confirmed the absence of sub-clusters. They revealed three minor atypical patterns at the boundaries between clusters, reflecting sensitivity to subtle parametric variations while maintaining overall structural coherence.

The simulation further identified the profile of the highest-performing agents in the

chatbot + emoji condition. These agents corresponded to participants with prior virtual training experience; more than two years of organizational tenure; familiarity with podcasts; at least two hours of study time per week; minimum technical education and prior exposure to conversational agents. This profile aligned with the empirical characteristics of participants who achieved the highest learning scores, confirming the convergence between the simulated and experimental phases and reinforcing the model's predictive validity.

Overall, these results indicate that the simulation reproduced the cognitive and socio-emotional mechanisms observed in the experimental phase. The strong correspondence between empirical and simulated outcomes confirms that combining chatbot support and expressive cues systematically enhances learning efficiency and persistence. The model provides a reliable computational tool for predicting learner behavior in digitally mediated corporate training environments and can be extended to explore future scenarios under different parametric configurations.

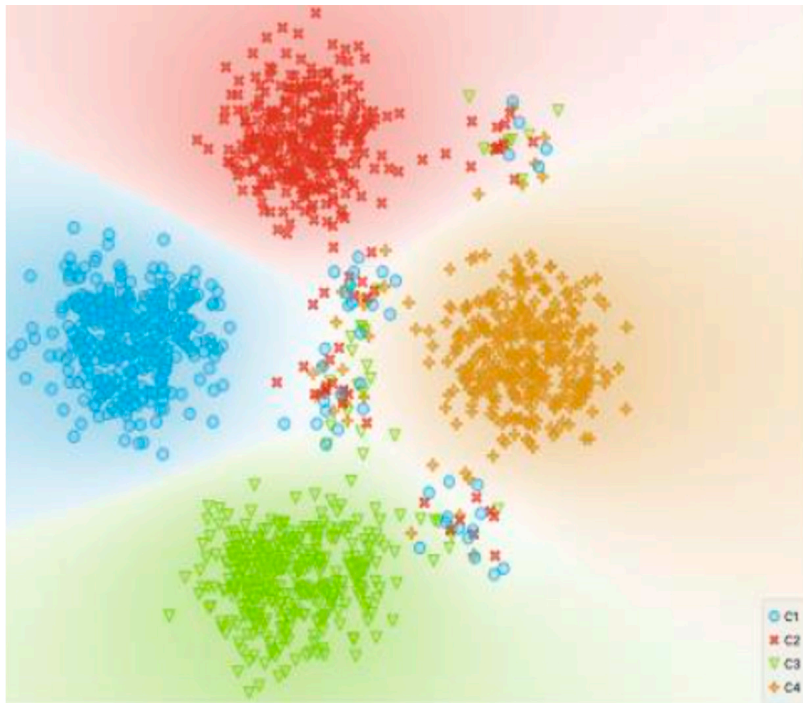


Figure 2. Cluster Groupings Generated by the Agent-Based Simulation Across the Four Chatbot and Emoji Experimental Conditions. *Source:* Own elaboration.

DISCUSSION

The study confirmed that the training generated meaningful and sustained learning gains. Participants showed substantial improvement from pretest to posttest, and the follow-up assessment indicated that this knowledge was retained 15 days after the program ended. This pattern suggests that the SPOC-based format and the instructional design supported both immediate comprehension and short-term knowledge consolidation, a finding that is consistent with prior research reporting instructional benefits and sustained value in digital training environments (Pihlainen et al., 2021; Seetal et al., 2021).

The experimental findings suggest that both chatbot use and emoji presence independently enhanced learning. The chatbot's positive effect is consistent with the Technology Acceptance Model, as instructional support may increase perceived usefulness and ease of use, thereby promoting stronger engagement with course activities and better performance (Ben Ammar & Neji, 2021; Sun et al., 2022; Yin et al., 2023). The positive contribution of emojis is also compatible with Social Presence Theory, since socio-emotional cues can reduce psychological distance and perceive digital communication feel more immediate and human (Garrison et al., 2000; Lowenthal & Borup, 2020). The present findings align with prior evidence showing that emojis enhance perceived warmth and relational closeness, which can support continuity and satisfaction in mediated learning processes (Kaye et al., 2021; Li et al., 2019; Park et al., 2022b).

The survival analysis highlighted persistence as a central outcome in corporate online training. Dropout concentrated in the first week, indicating that early participation is the most vulnerable stage. The chatbot-plus-emoji condition showed the highest survival and the lowest dropout risk, suggesting that functional support and socio-emotional signaling jointly sustained continuity in the asynchronous environment, consistent with prior work on digital engagement and social presence (Ben Ammar & Neji, 2021; Lowenthal & Borup, 2020; Sun et al., 2022; Yin et al., 2023). The Cox models further indicated that prior podcast use and previous virtual training experience acted

as protective factors, in line with evidence that familiarity with mediated learning supports persistence over time (Park et al., 2022a).

The agent-based simulation reinforced the experimental findings by reproducing the same performance hierarchy across the four conditions. The results indicated that the chatbot required sufficient usability, adaptability, and functionality to improve learning, in line with prior work on technology acceptance and digitally mediated learning support (Ben Ammar & Neji, 2021; Sun et al., 2022; Yin et al., 2023). Although simulated dropout rates were lower than those observed in the training program, the relative attrition pattern remained stable, supporting the model's internal coherence and explanatory value.

The profile of high-performing agents closely matched the empirical data. Participants with prior virtual training experience, longer organizational tenure, familiarity with podcasts, and regular weekly study time were more likely to belong to the high-performance cluster. This convergence strengthens the explanatory value of combining experimental and computational evidence and is consistent with prior research showing that familiarity with digitally mediated learning supports continuity and stronger learning performance over time (Park et al., 2022a; Pihlainen et al., 2021).

Overall, the findings indicate that corporate e-learning can benefit from combining cognitive scaffolding with socio-emotional cues, particularly during the early stages of participation, when dropout risk is the highest. In the present study, this combination was associated with lower attrition and stronger learning outcomes. These results are consistent with previous studies showing that instructional support improves engagement and performance, while socio-emotional signaling reduces psychological distance and supports continuity in digitally mediated learning (Ben Ammar & Neji, 2021; Lowenthal & Borup, 2020; Park et al., 2022b; Sun et al., 2022).

These findings should be interpreted within the boundaries of the study's design and context. The experiment was conducted within a single organization and a specific corporate training program, which limits the direct generalization of results to other industries, organizational cultures, or instructional settings. Rather

than generalizing universal effects, the results provide context-dependent evidence regarding the role of cognitive and socio-emotional support in asynchronous corporate e-learning.

CONCLUSIONS

This study provides evidence suggesting that integrating a chatbot with socio-emotional cues, such as emojis, was associated with higher learning outcomes and lower dropout rates within the context of a corporate virtual training program. The chatbot acts as a cognitive scaffold, supporting comprehension and engagement by increasing perceived usefulness a core component of the Technology Acceptance Model. Emojis, in turn, seem to contribute an independent socio-emotional effect by humanizing interactions and reducing psychological distance, consistent with Social Presence Theory.

The agent-based simulation reproduced the empirical structure observed in the experimental phase and provided analytical coherence to the identified learning and dropout patterns. It replicated the performance ranking observed in the training phase and identified the characteristics of the highest-performing participants: prior virtual training experience, organizational tenure of at least 2 years, familiarity with podcasts, and consistent weekly study habits. This convergence between empirical and simulated results suggests that the underlying cognitive and socio-emotional mechanisms of chatbot and emoji use can be represented computationally with internal coherence.

Taken together, these findings indicate that instructional designs integrating functional support with socio-emotional signaling may enhance learning efficiency and persistence during the early stages of remote corporate training, when dropout risk is the highest. These results provide a basis for refining corporate virtual training models, particularly in operational contexts with historically low digital adoption. These conclusions are constrained by the study's design and context and should not be interpreted as universal effects across all corporate or educational settings.

Future research should seek to replicate these findings across other industries, incorporate larger, more diverse samples, and extend the computational model to explore a broader spectrum of usability and adaptability parameters. Organizations considering chatbot-supported training should also assess the technological and emotional readiness of their workforce, as the efficacy of these systems is fundamentally shaped by how employees perceive the human dimension in automated interactions.

Conflicts of Interest

The authors declare no conflicts of interest.

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Authors' contributions:

Conceptualization: MML, FMC; Data Curation: LCAP, JCV, JAHM, JCVM; Formal Analysis: MML; Research and Methodology: MML, FMC; Project Management: MML, LCAP; Resources: LCAP; Software: JCV; Supervision: MML, FMC; Validation and Visualization: JCVM; Writing - Original Draft: MML, FMC, JCVM; Writing - Review and Editing: JCVM.

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